LARS Technical Report 012477

Crop Identification and Area Estimation over Large Geographic Areas Using LANDSAT MSS Data

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16. Abstract

This report describes the results of a study involving the use of computer-aided analysis techniques applied to Landsat MSS data for identification and area estimation of winter wheat in Kansas and corn and soybeans in Indiana. Key elements of the approach included use of aerial photography for classifier training, stratification of Landsat data and extension of training statistics to areas without training data, and classification of a systematic sample of pixels from each county. Major results and conclusions are that (1) Landsat data was adequate to accurately identify winter wheat in Kansas, but not corn and soybeans in Indiana; (2) computer-aided analysis techniques can be effectively used to extract crop identification information from Landsat MSS data, and (3) systematic sampling of entire counties made possible by computer classification methods resulted in very precise area estimates at county as well as district and state levels.

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PREFACE

This investigation applied to Landsat data the advances and developments of the past decade in analyzing multispectral remote sensing measurements for crop identification and area estimation. Landsat MSS data for Kansas and Indiana were classified using computer-aided analysis techniques to identify and determine the areal extent and distribution of the major crops in the two state test area. It was conclusively demonstrated that Landsat data analyzed by computer methods could be effectively used to produce accurate estimates having extremely small sampling error. Recommendations are made for increasing the spectral, spatial and temporal resolution of data acquired by future satellite systems, along with preprocessing to geometrically correct and register data sets. It is recommended that attention be given to developing more effective methods of scene stratification and obtaining crop yield information from Landsat data.

The rationale and background of the investigation are described in Section 1.0; the objectives follow in Section 2.0. In Sections 3.0 and 4.0 the test areas and experimental approach and procedures are described. The results of the investigation are presented in Sections 5.0 and 6.0. The significant results and conclusions of the investigation are given in Section 7.0, followed by the recommendations in Section 8.0.

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1.0 INTRODUCTION

As our grain reserves become depleted and world population and demand for food increase, the need to improve the quality of world crop production information becomes ever more critical. Accurate and timely crop production information has been identified at the World Food Conference held in Rome in 1974 [25] and more recently in a National Academy of Science study [20] as a critical part of the solution of the food problem.

During the past decade considerable evidence has developed that multispectral remote sensing from aerospace platforms can provide quantitative data which can be effectively used to identify major crop species and determine their areal extent. Remote sensing techniques may prove to be a more accurate, precise, timely, and/or cost effective method of acquiring crop production information than conventional surveys carried out on the ground. The information gained from this investigation should provide additional data on which to determine the utility of remote sensing.

1.1 Value of Crop Production Information

Most countries forecast and estimate their crop production, but relatively few have reliable methods for gathering the necessary data. The benefits of improved crop information are: (1) accurate estimates result in price stability; (2) timely and accurate forecasts of production allow governments to plan domestic and foreign policies and actions; and (3) accurate forecasts enable optimal utilization of storage, transportation, and processing facilities. Conversely, the socioeconomic costs of not having accurate and timely information available are substantial.

The economic value of increased crop forecast accuracy in the United States was first quantified by Hayami and Peterson [12]. They estimated from their model that a reduction in forecast error for wheat from 3.2% to 2.1% would have annual net social benefits of 70 million dollars at 1968 prices--a figure which would be approximately doubled at 1974-1976 prices. On a world basis the value of improved forecast would be substantially greater. Comparable benefits would be gained by improving the accuracy of estimates for other major crops.

In addition, more frequent information, such as might be provided with remote sensing techniques, would increase the social benefits even without improvements in the crop estimate error [10].

1.2 Conventional Crop Survey Methods

Information gathering is as old as civilization. Census taking by the Egyptian Pharaohs and Roman Emperors are good examples. However, the application of scientific statistical methods to gathering agricultural statistics is only about a hundred years old. But, in spite of many technological advances in the methods used to survey crops, many countries still do not have adequate systems to gather data needed to support satisfactory decision making about food and nutrition.

The system developed in the United States is regarded as being one of the most comprehensive and accurate. In this country the Statistical Reporting Service of the Department of Agriculture (USDA/SRS) has responsibility for collecting and reporting current data on U.S. agriculture. The present program of crop and livestock estimation annually includes over 500 national reports, plus numerous reports issued by individual states. Reports are made for more than 120 crop commodities (including field and seed crops, vegetables, fruits, and nuts) and provide estimates of acreages farmers intend to plant; acreages actually planted and harvested; yield, production and crop disposition; as well as periodic indications of remaining stocks for important crops. Monthly forecasts of production are prepared for major crops throughout the growing season.

Nearly all surveys conducted by SRS are probability surveys based on relatively small samples. Since 1965 a national general purpose survey including 17,000 area segments which are enumerated during May and June each year has been used. The sampling units or area segments are typically about 2.6 square kilometers (about one square mile) in size. This sample is stratified with states and areas within states serving as strata. Crop reporting districts(CRD), groupings of contiguous counties having similar agricultural practices, are generally the intrastate strata. Sample selection within strata follows a systematic approach using a geographically arranged listing of the sampling frame. Trained enumerators visit each segment and interview each farm operator to obtain data on crop acreages, livestock production, production costs, and prices received. About 20% of the questionnaire concerns crop acreage information. Additional information describing the SRS sampling and estimation procedures may be found in references [23] and [7].

The current SRS probability surveys provide independent estimates with known measures of precision (sampling errors). Typical sampling errors for several major crops are shown in Table 1. It should be noted here the SRS surveys are designed to produce accurate, precise estimates at the national level. At the state level where there are generally 300-400 sampling units, the sampling error is

Table 1. Coefficients of variation from June Enumerative and Objective Yield Surveys in the United States, 1975.[a]

	Coefficient of Variation (%)		
Crop	Acres Planted	Yield	Production
Winter Wheat	1.5	1.0	2.0
Corn	1.1	0.9	1.7
Soybeans	3.5	1.0	2.1
Cotton	3.5	1.0	3.7

[a]From Caudill [7].

greater; coefficients of variation are typically 4-6%.

Estimates for counties are not obtained from the June enumerative survey since there are too few segments per county to be reliable. Rather, the estimate of the total acreage of, for example, wheat in the state is obtained and then subdivided among counties. The county allocations are based on a mail survey which may include 50-100 respondents per county and/or the last agricultural census. Variance estimates are not calculated by the SRS for county estimates, but the coefficients of variation are believed to be on the order of 10% or more.

1.3 Development of Remote Sensing Technology for Crop Surveys

To understand the approach used and results from this investigation it will be helpful to briefly review the development of remote sensing technology related to crop surveys. This historical perspective will indicate the progress which has been made and the contribution of this investigation.

Remote sensing from satellites is particularly appropriate for crop surveys because of the capability to obtain repetitive coverage of wide areas. The physical basis for remote sensing, data acquisition platforms and sensors, and data analysis techniques are described by Bauer [3] in a review of the potential role of remote sensing in determining the distribution and yield of crops.

Remote sensing as it is known today is an outgrowth of aerial photography. Although the use of aerial photography has been developing for more than a hundred years, remote sensing has been evolving and expanding most rapidly since 1960 as new sensors and interpretation techniques became available.

In 1964, multispectral photography was collected for the first time over agricultural fields, and the potential of the multispectral approach to crop identification was recognized [13]. After this approach was further defined, a crop classification was made from multispectral scanner data in 1967, using pattern recognition methods implemented on a digital computer [17].

One of the first investigations using satellite-acquired imagery to identify crops was performed by Anuta and MacDonald [2]. Apollo-9 multispectral photography was digitized and analyzed using computer-implemented pattern recognition techniques. Agricultural land in the Imperial Valley of California was accurately classified into several individual crops, soil, and water.

The Corn Blight Watch Experiment, conducted in 1971 by NASA, USDA, Purdue University, and the University of Michigan in seven Corn Belt states, provided a prototype remote sensing system [18]. It successfully integrated techniques of sampling, data acquisition, storage, retrieval, processing, analysis, and information dissemination in a quasi-operational system environment. The results showed that remote sensing could be used to quantitatively recognize corn leaf blight, as well as other agricultural crops and land uses over broad areas.

The supply of remotely sensed data greatly increased with the launch of Landsat-1 (formerly called the Earth Resources Technology Satellite or ERTS-1) in 1972. From an orbit 912 km above the earth, the satellite can complete a full observation of the earth every 18 days. Its multispectral imagery is collected in four visible and infrared wavelength bands over 185 km wide passes over the earth. This newest data source with its synoptic view of earth has opened a whole new dimension to the capability to obtain information about earth resources.

Bauer and Cipra [4] used multivariate pattern recognition methods implemented on a digital computer to classify Landsat-1 data acquired over a three-county area in northern Illinois. The classification of the Landsat data, as measured by an independent sample of test fields, was 85% accurate on a point by point basis (Table 2). Although there were errors in the classification of individual data points, area estimates made over the three-county area were within a few percent of those made by the U.S. Department of Agriculture (Table 3).

Table 2. Classification of corn, soybean, and "other" test fields by computer-aided analysis of Landsat-1 multispectral scanner data for DeKalb County, Illinois.[a]

Crop	Number of points	Number of points classified as Corn	Soybeans	"Other"	Percent correctly classified
Corn	3968	3367	357	244	85
Soybeans	1113	115	855	133	77
"Other"	295	16	50	234	79
	5376	3498	1262	611	83

[a]From Bauer and Cipra [4].

Table 3. Comparison of area estimates made by U.S. Department of Agriculture and from classification of Landsat-1 multispectral scanner data for DeKalb, Ogle, and Lee Counties, Illinois.[a]

Crop	Percent of total area USDA	LANDSAT
Corn	40.2	39.6
Soybeans	18.0	17.8
Other	41.8	42.6

[a]From Bauer and Cipra [4].

2.0 OBJECTIVES

The long term objective of this investigation is to develop and test procedures utilizing Landsat data to not only identify, but more importantly, determine the areal extent and distribution of earth surface features over large geographic areas. The specific applications selected for this investigation are crop identification and area estimation for two states in the Central United States.

There is high probability that improved crop production information, long recognized as a potential application of remote sensing, can be obtained from Landsat data. The wide area coverage of Landsat, linked with computer processing, offers a unique opportunity to improve upon the sampling methods now used for making area estimates from ground-based systems. This is particularly true as the size of the area decreases, e.g. state, district, county. Further, the sequential coverage of Landsat should lead to improvements in the timeliness of the estimates. Both of these aspects would result in economic and social benefits.

The specific objectives of this study are:

- Using Landsat data and computer-implemented pattern recognition, classify the major crops from regions encompassing different climates, soils, and crops.
- Estimate crop areas for county and state size areas using the crop identification data obtained from the Landsat classifications.
- Evaluate the accuracy, precision, and timeliness of crop area estimates obtained from Landsat data.

Two important underlying premises to be tested in the investigation are:

- The synoptic view of Landsat provides the opportunity to obtain crop production information over large areas, e.g. states and countries.
- By using computer-implemented data analysis to classify pixels distributed over entire counties, it is also possible to make accurate and precise estimates for local areas, e.g. counties.

The successful accomplishment of the investigation would contribute to the development of earth resources surveys by:

- Leading to operational use of satellite data for obtaining crop area estimates.
- Refining techniques which could also be applied to other problems such as crop yield forecasts, natural resource inventories, and measurement and monitoring of damage caused by floods, drought, insects and disease.
- Developing improved methods of obtaining necessary ground truth.
- Testing statistical sampling models designed specifically for remote sensing applications.
- Providing data for determining needed information on costs and benefits of obtaining information using remote sensing.

3.0 SELECTION AND DESCRIPTION OF TEST AREAS AND CROPS

Kansas and Indiana were selected as the test states for this investigation. Winter wheat in Kansas and corn and soybeans in Indiana were selected as the crops for which area estimates would be made from classifications of Landsat data.

The test areas and crops were selected to sample the range of conditions which are present in the Great Plains and Corn Belt regions of the United States. The selections of test areas and crops were made taking into account the spectral and spatial parameters of the Landsat data and the characteristics of crop production. On the "spectrum of difficulty", wheat identification in Kansas is undoubtedly an easier problem than corn and soybean identification in Indiana. That is, the Landsat data is likely to be more adequate for winter wheat identification in Kansas than for corn and soybean identification in Indiana.

Winter wheat is the first crop to "green-up" in the spring, has the greatest amount of green biomass (except for alfalfa) during the April to mid-June period, and at maturity in late June and early July is the only cover type which is golden-yellow in color. In other words, during much of its growth cycle it is dissimilar from the other cover types present. Additional factors simplifying the task of wheat identification and area estimation in Kansas is that wheat is grown in relatively large fields, on a large percentage of the agricultural land, and with relatively few other cover types and crops present.

In comparison, corn and soybeans in Indiana are warm season or summer crops which are green at the same time as many other cover types present during the summer in Indiana. Some of the possible "confusion" cover types include trees, pasture, forage crops, and oats. Secondly, field sizes in Indiana are much smaller than in Kansas. This is due to the greater heteorogeneity in soils and the greater number of crops being grown. The smaller field sizes cause a greater fraction of pixels to fall on field boundaries and include more than one cover type. In summary, corn and soybeans in Indiana are more like the classes they are to be discriminated from than is the case with winter wheat in Kansas.

Kansas is the number one wheat producing state in the nation [16]. Its wheat production for 1975 totaled 9.6 million metric tons (351 million bushels), 10% above 1974 and second only to the record 10.5 million metric tons (385 million bushels) produced in 1973. The 1975 crop was seeded on 5.2 million hectares (12.8 million acres), 7% more than a year earlier. Area harvested for grain, at 4.9 million hectares (12.1 million acres), was 4% above the previous year.

Abandonment, at 5.5%, was slightly above recent years but well within normal rates of abandonment. The average yield of 19.5 quintals per hectare (29 bushels per harvested acre) was 1.0 quintal (1.5 bushels) above the 18.5 quintal (27.5 bushel) average in 1974. The distribution of wheat production in the state is shown in Figure 1. The farm value of the 1975 wheat crop in Kansas was 1.2 billion dollars.

Kansas soils were developed under mixed or short prairie grass vegetation. Average precipitation varies from 38 centimeters (15 inches) in the west to 81 centimeters (32 inches) in the east. The climate is continental in most of the state, becoming semi-arid in the west. The distribution and amount of precipitation during the year fit the requirements of winter wheat better than any other crop in much of the state. Other important crops grown include corn, grain sorghum, and alfalfa. The amount of irrigated land is increasing each year. There were 20.2 million hectares (49.9 million acres) of land in farms in 1975; crops were harvested from 12 million hectares (30 million acres).

In 1975 Indiana ranked third among the states in both corn and soybean production [15]. The 2.3 million hectares (5.6 million acres) of corn harvested was a record high. The average corn yield was 59 quintals per hectare (98 bushels per acre). Production at 13.5 million metric tons (552 million bushels) was the second largest crop on record. The area in

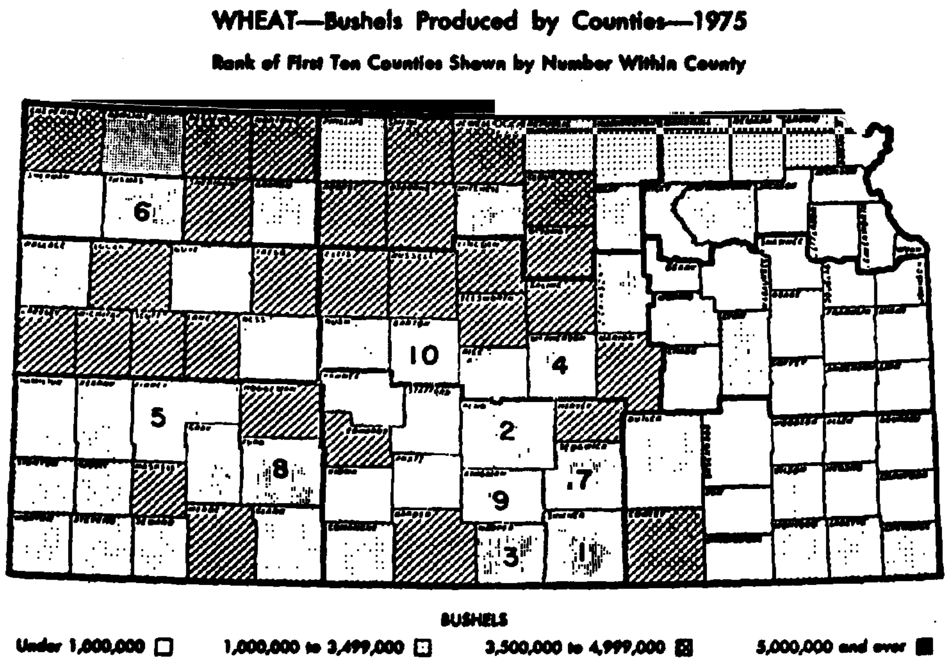


Figure 1. The distribution of 1975 wheat production in Kansas.

soybeans was 1.5 million hectares (3.6 million acres), 7% below the previous year. The 20.7 quintal (33 bushel) average yield was a record high and total production of 3.0 million metric tons (120 million bushels) was the second greatest ever. The distributions of Indiana corn and soybeans are shown in Figure 2.

Indiana includes both glacial and non-glacial soils, with topography ranging from the nearly level prairies of northern and central parts of the state to the rolling and steep lands of the southern areas of the state. Both dark colored soils developed under prairie vegetation and light colored soils developed under forest are present. The climate is typically continental with cold winters, warm summers, and frequent short period fluctuations of temperature, humidity, cloudiness, and wind direction. The well-distributed annual precipitation of 81 to 102 centimeters (32 to 40 inches) favors high agricultural production. Sunshine averages more than 70% of its possible duration for the summer months and summer precipitation occurs mostly during short duration showers or thunderstorms.

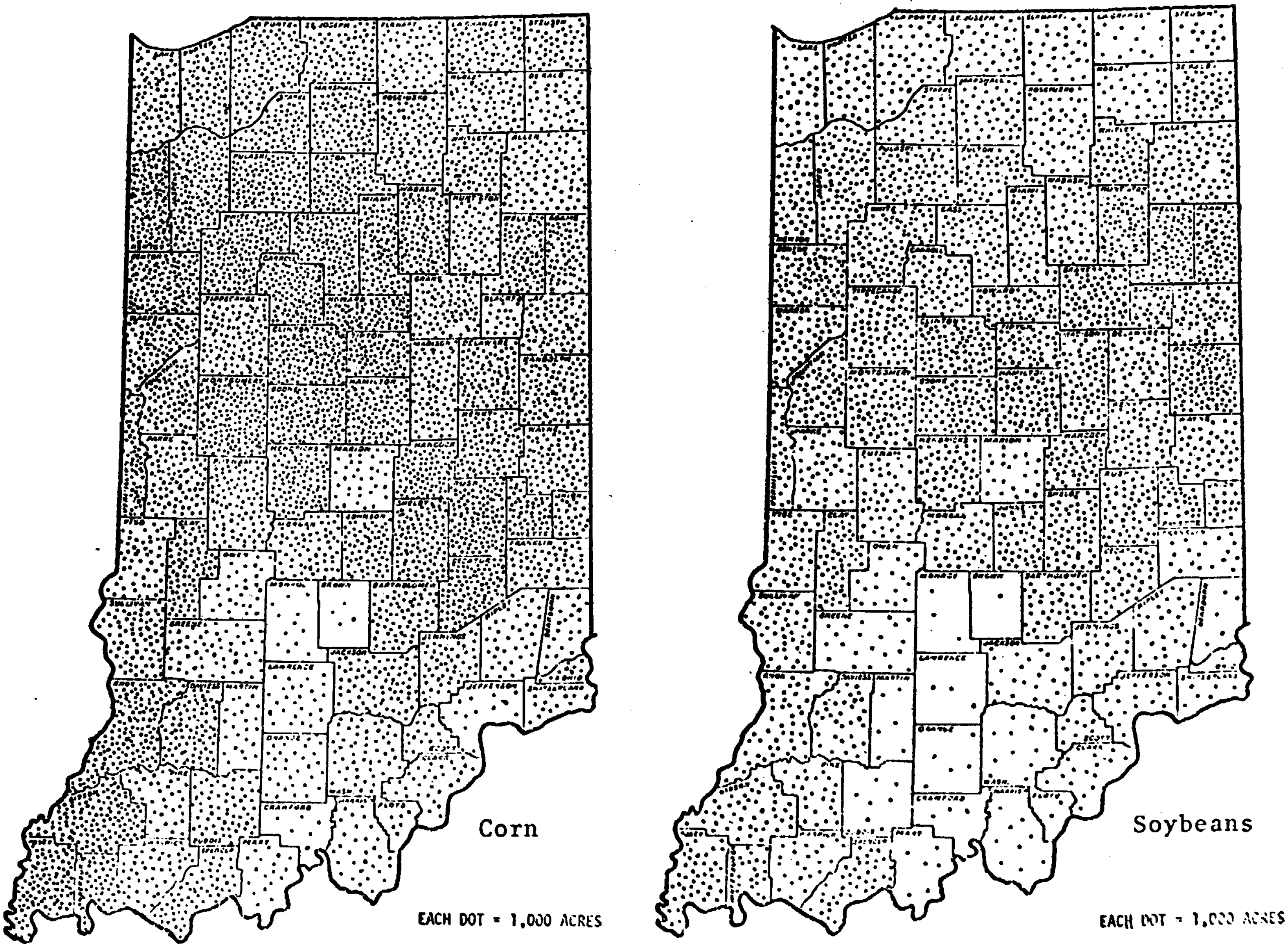


Figure 2. Corn and soybeans acreage harvested in Indiana, 1975.

4.0 EXPERIMENTAL APPROACH AND PROCEDURES

The approach used in the investigation built on procedures developed and utilized in previous research at LARS with the objective of extending them to larger areas. The procedures were developed upon five fundamentals which were determined early in the investigation:

- The classifier would be trained and tested using aerial photography as reference data.
- Counties without reference data would be classified using training statistics from an adjacent county having similar crops and soils and lying in the same Landsat frame.
- Area estimates would be made from a systematic random sample of pixels distributed over the entire county.
- Area estimates would be made on a county basis and aggregated to district and state levels.
- Estimates would be adjusted for classification bias.

The implementation of the basic steps is illustrated in Figure 3. The remainder of this section describes in detail the procedures used in the investigation.

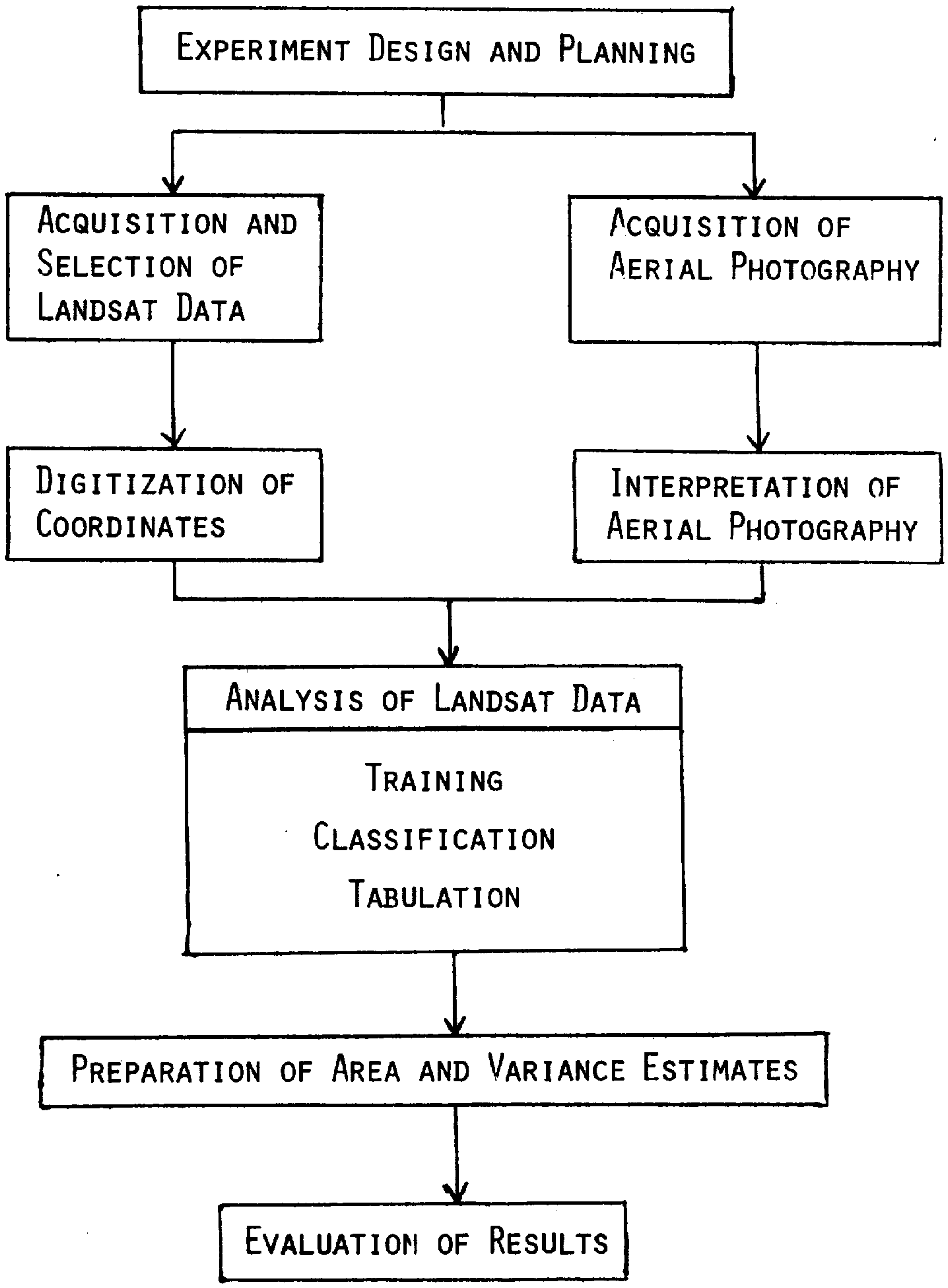


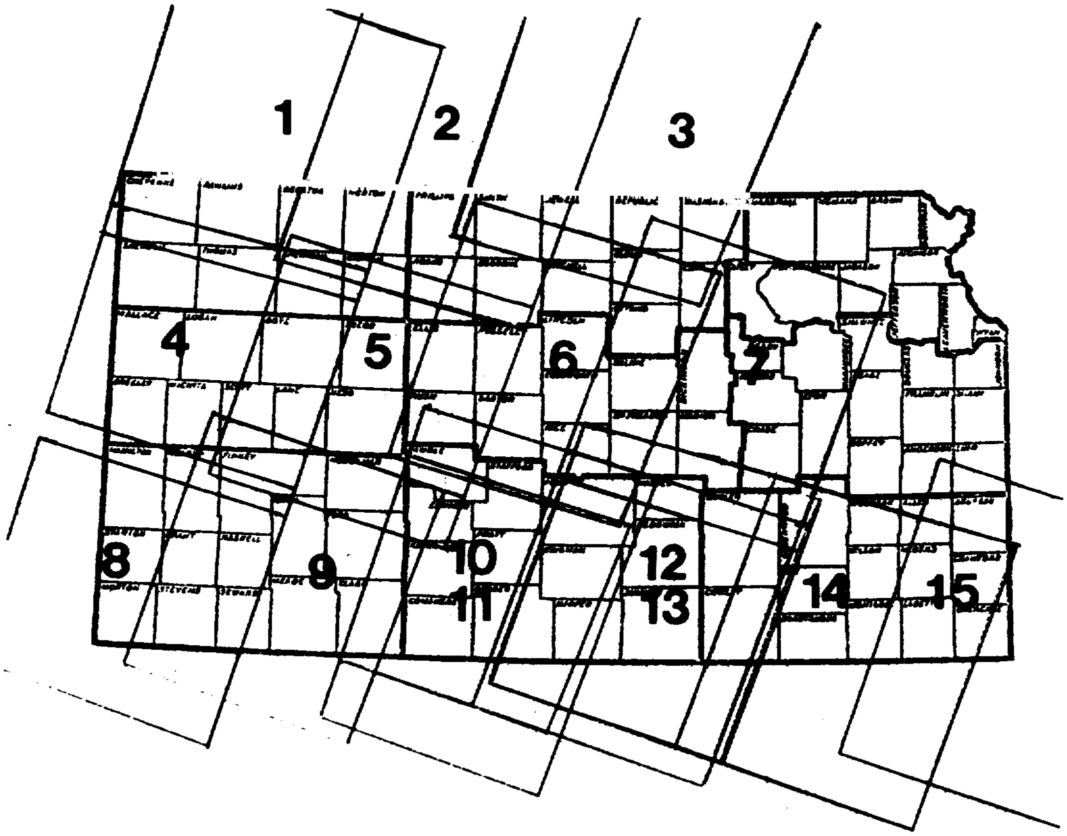
Figure 3. Implementation of experimental approach.

4.1 Acquisition and Selection of Landsat Data

At the beginning of the project a standing order was placed with the EROS Data Center for Landsat-2 photographic imagery over Kansas and Indiana. The imagery was the basis for decisions of the choice of scenes to be used for classification. If a scene was chosen for use, the bulk computer compatible tape was then ordered retrospectively. Landsat-2 was the primary source of multispectral scanner (MSS) data, with Landsat-1 scenes being used only to complete the coverage for the Southwestern Crop Reporting District (CRD) in Kansas.

The selection of a Landsat frame to classify for a given county was based upon the date of the Landsat data, the location of ground truth, and the amount and location of cloud cover. The desired attributes were that the crops of interest were spectrally discriminable at the time of the Landsat pass; aerial photography was available over areas similar in crop stage and soils in the same frame; and both the county to be classified and the training areas were not obscured by clouds or bad data.

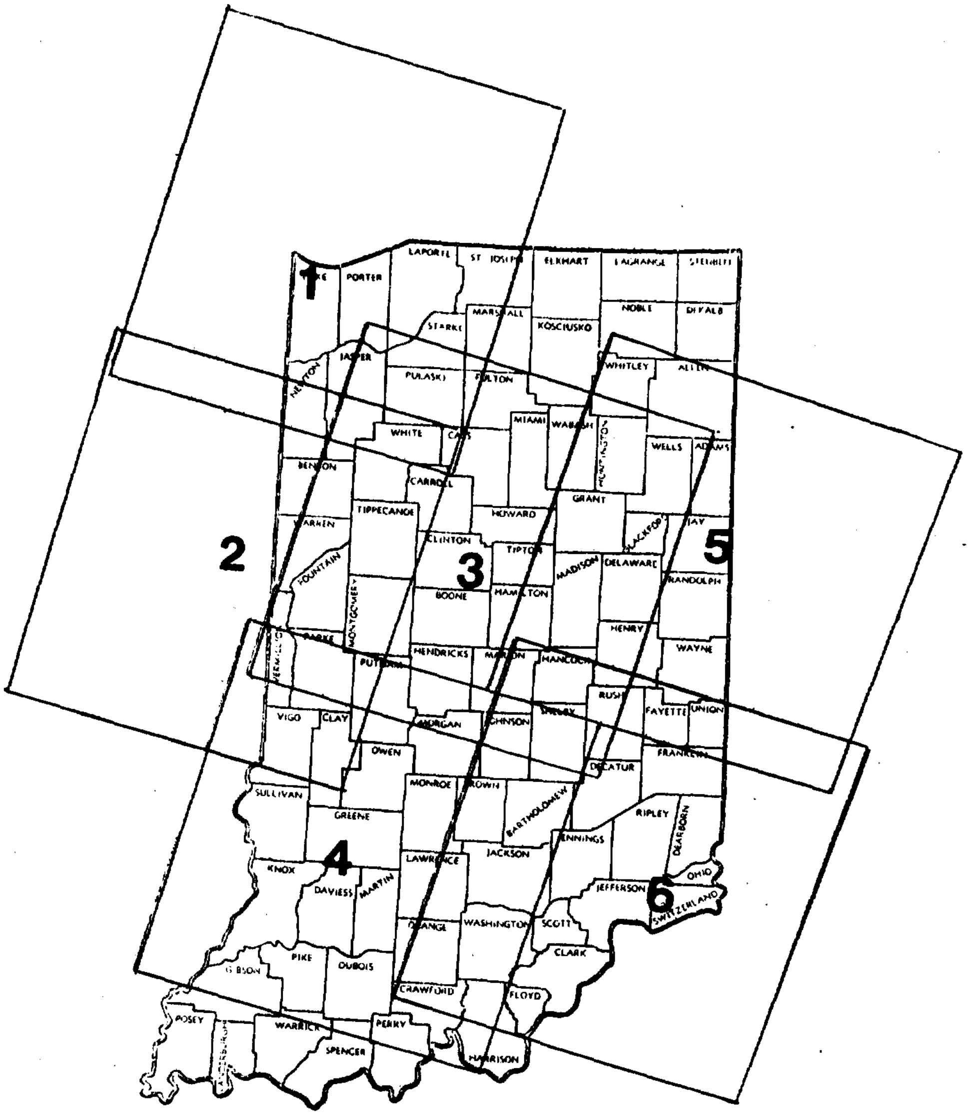
The Landsat frames chosen for the analysis in Kansas and Indiana are shown in Figures 4 and 5, respectively. The amount of cloud cover created a serious problem for obtaining data for much of Indiana and northeastern Kansas. As a result, satisfactory data was not available for the Northeast



Key

	Landsat Scene ID	LARS Run Number	Date
1	2165-16450	75013800	July 6
2	2146-16392	75005800	June 17
3	2163-16334	75006500	July 4
4	2165-16453	75004600	July 6
5	2146-16395	75005900	June 17
6	2163-16340	75006600	July 4
7	2144-16282	75005600	June 15
8	2147-16460	75006200	June 18
9	5032-16310	75007200	May 21
10	2073-16342	75001500	April 15
11	2109-16341	75005000	May 11
12	2072-16284	75000900	April 9
13	2144-16284	75005700	June 15
14	2107-16225	75004900	May 9
15	2142-16171	75005400	June 13

Figure 4. Landsat Coverage for Kansas.



Key

	Landsat Scene ID	LARS Run Number	Date
1	2228-15515	75009100	September 7
2	2228-15522	75009200	September 7
3	2209-15464	75009000	August 19
4	2173-15480	75008700	July 14
5	2208-15405	75010000	August 18
6	2208-15412	75010100	August 18

Figure 5. Landsat Coverage for Indiana.

and East Central CRDs in Kansas. In Indiana, the only districts that had complete Landsat coverage were the Northwestern, West Central, Central and East Central.

Tables 4 and 5 illustrate the cloud cover problem. The standing order for Landsat-2 photographic imagery requested scenes that contained less than 50% cloud cover. Since a low cloud cover percentage does not necessarily mean that a scene is usable for analysis, the number of usable scenes is specified in Tables 4 and 5. For example, a frame could be half in Indiana and half in Illinois. If the frame has 10-20% cloud cover but the clouds cover the Indiana portion of the frame, it is unusable. Or, if there are three or four large cloud patches which occur as long streaks across the frame, the frame is unusable even though the cloud cover may have only been 20%. The magnitude of the cloud cover problem is indicated in the tallies of data acquired and data used which show that only 21 out of 93 frames in Kansas and only eight out of 40 in Indiana were usable.

In Kansas, there was April data available to cover the entire south central CRD and data in May and June to provide duplicate coverage for ten of the thirteen counties. It was decided to analyze these ten counties twice and compare the results. Figure 4 indicates which counties were analyzed twice and which frames and dates were used. In the statistical analysis of the results for Kansas, both dates were used for most of the statistical tests. However, the tables

Table 4. Summary of acquisition and usability of Landsat-2 data for Kansas, April 1 - July 17, 1975.

Month	No. Frames Acquired by NASA/GSFC	No. Frames Received from EROS Data Center*	No. Usable Frames
April	29	8	6
May	28	9	2
June	18	15	9
July	18	9	4
Total	93	41	21

*Standing order for all frames with < 50% cloud cover.

Table 5. Summary of acquisition and usability of Landsat-2 data for Indiana, July 1 - September 7, 1975.

Month	No. Frames Acquired by NASA/GSFC	No. Frames Received from EROS Data Center*	No. Usable Frames
July	14	11	2
August	16	7	4
September	10	6	2
Total	40	24	8

*Standing order for all frames with < 50% cloud cover.

in sections 5.2 to 5.3 display figures only for the second date for these ten counties since the second date was closer to the time the wheat was harvested. The estimates made at harvest time are more important since the SRS estimates for area harvested were used for comparison of results.

4.2 Acquisition of Aerial Photography

A critical part of the entire investigation involved the reference or "ground truth" data set to be utilized in conjunction with the computer-aided analysis of the Landsat MSS data. Reference data was required for training the classifier and to test the accuracy of classification. Detailed crop type maps do not exist because the crop grown in an individual field generally changes each year. And, indeed some field boundaries are changed from year to year. Therefore, current reference data sets had to be acquired to support the planned Landsat data analysis.

In many previous agricultural remote sensing experiments, reference data were obtained by on-the-ground identification and recording of crop type and other information by the researchers or local USDA personnel. But, the amount of data which can be obtained in this way is restricted by the time and personnel available and generally can be done for only a few relatively small areas. Resources were not available to implement such an effort, even using sampling, for two entire states.

During the CITARS project conducted by NASA/JSC, LARS, and ERIM, this type of ground observations was supplemented by interpreting aerial color infrared photography acquired concurrently and over the same area as the ground observations [5]. The accuracies of crop identification by photo-interpretation routinely exceeded 95% and the data were successfully used for training and test purposes. It was therefore decided to take this approach one step further and make aerial photography the primary reference data source to identify and locate samples of wheat, corn, soybeans, and other cover types in the Landsat data.

After studying soil, climatology, and land use maps, flightlines were selected throughout each state to sample the variation in soils, land use, and crops. The flightlines were oriented north-south following major highways in Kansas and Indiana so that the aerial photography and Landsat data could be coordinated easily.

A 70 mm Hulcher two-camera system was used with color infrared and color transparency film. The average ground speed was 275 km per hour and photographs were taken, with both cameras, at intervals of 38 seconds, producing a continuous strip of imagery with an overlap of 25-30%. The average altitude for each flight mission was 3,000 meters. The approximate scale of the photography was 1:80,000. Each frame of aerial photography included an area roughly four kilometers square (2.5 x 2.5 square miles). Examples of the photography are shown in Figures 10 and 11.

In Kansas, aerial photography was acquired on April 29-30 and June 26-27. Both dates were quite adequate for differentiating wheat from all other cover types. The June mission covered the eastern counties (and some western counties) while the April one covered the rest of the state (Figure 6).

The flightlines and dates of aerial photography acquisition for Indiana are shown in Figure 7. The May photography, when used concurrently with the July or August photography, helped to differentiate corn and soybeans from all other fields.

4.3 Digitization of Coordinates

The Landsat coordinates for county boundaries were needed in order to make county crop estimates. In addition, three to eight points were needed along the flightline in a county in order for the analyst to match a computer map of Landsat data to the aerial photography. To find coordinates, the following procedure was used:

1. Determine which counties are contained in the Landsat scene.
2. Locate 25-30 checkpoints in the Landsat scene.
3. Digitize these checkpoints on a 1:250,000 USGS map.

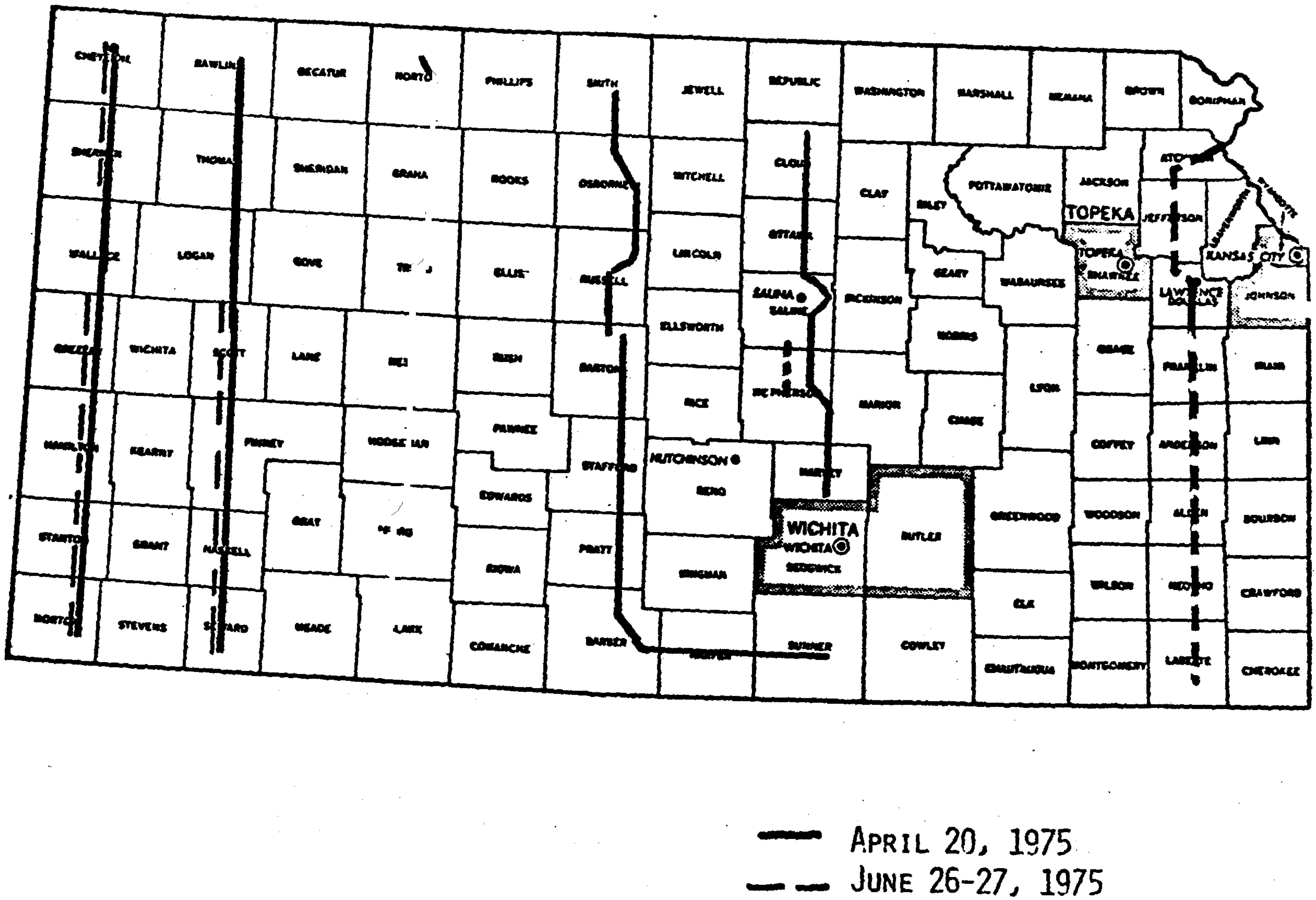


Figure 6. Kansas aerial photography flightlines and dates of photography acquisition.

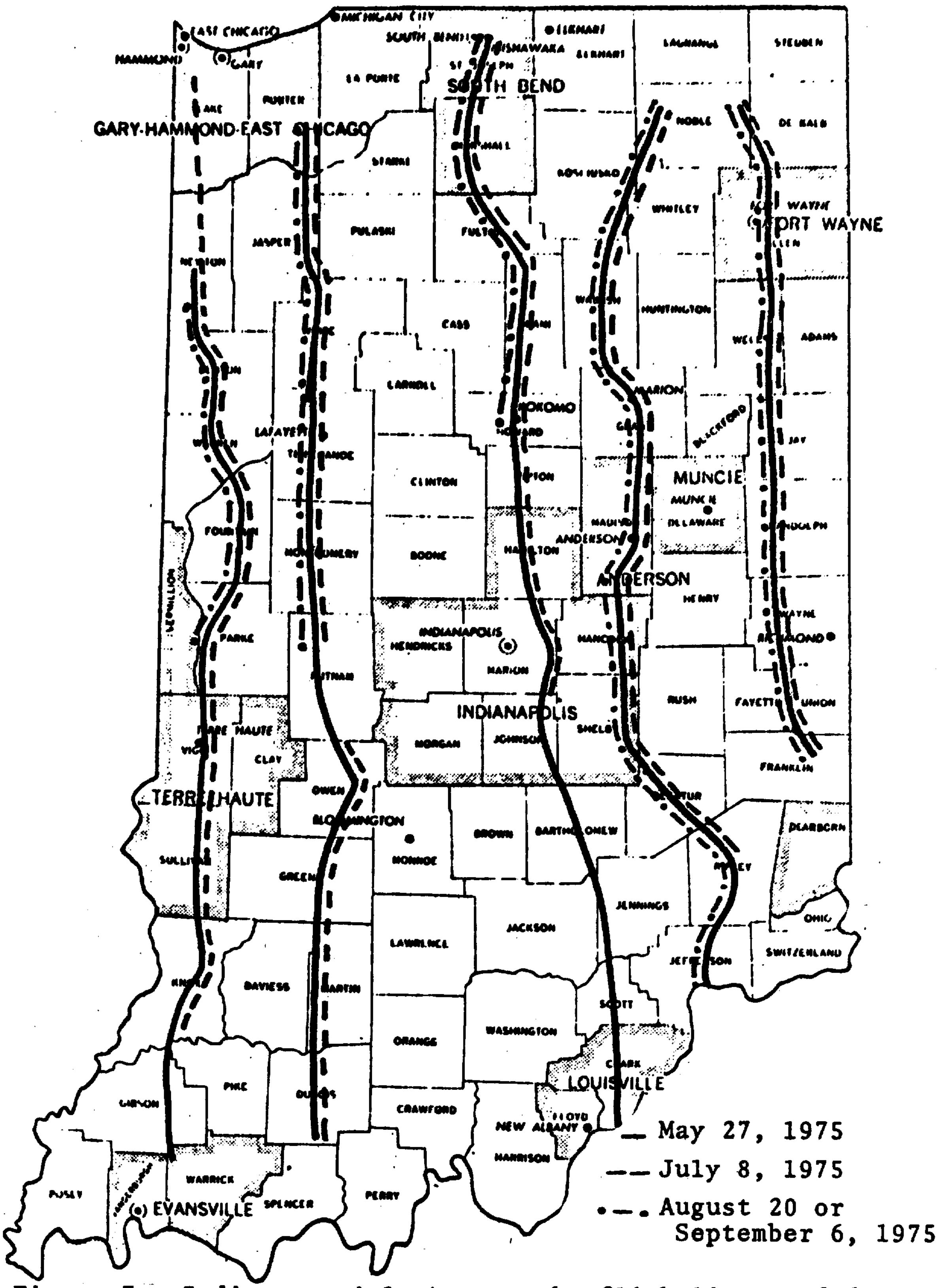


Figure 7. Indiana aerial photography flightlines and dates.

4. Digitize points defining county boundaries.

5. For each county that has aerial photography, digitize three to eight points along the flightline.

6. Use a bivariate quadratic regression routine to fit coordinates of the checkpoints from the Landsat scene to the corresponding coordinates on the USGS maps. Then calculate Landsat coordinates for points defining county boundaries and checkpoints along the flightline.

7. Record the Landsat coordinates for county boundaries, and mark the Landsat coordinates for flightline points on the county maps.

In the following paragraphs each of the steps is described further.

The outlines of the state and all the county boundaries are displayed on a digital display device. Using the latitude and longitude for the Landsat scene center, the outline of the scene can be superimposed. A photograph taken of this image aids in determining which counties are covered.

In order to locate checkpoints, the data was displayed one channel at a time, in 16 gray levels. Twenty-five to 30 checkpoints were found, generally at the intersection of two highways, and the Landsat coordinates of these points were recorded.

The (x,y) coordinates of the checkpoints found in the Landsat scene, the points defining the county boundaries, and additional checkpoints along the flightlines are obtained from USGS 1:250,000 scale maps. A regression routine was used to fit the Landsat checkpoints to the checkpoints digitized from the USGS maps. The Landsat coordinates of the county boundaries and additional points along the flightlines were then listed and recorded on maps (Figures 8 and 9). The Landsat coordinates of the county boundaries were later used for tabulating county classification results. The coordinates of the points along the flightlines were used by the analysts to locate the flightlines in the Landsat data.

4.4 Interpretation of Aerial Photography

Large scale aerial photography was used as reference data following the assumption that the crops of interest could be readily and accurately identified. Standard photointerpretation techniques were used to identify fields of wheat and nonwheat in Kansas and fields of corn, soybeans, and "other" in Indiana. The coordinates of the identified fields were then located in Landsat data. Wheat was relatively easy to identify in Kansas; corn and soybeans were more difficult to identify in Indiana. Fields which were not positively identified were not included as either training or test fields. Problems in photointerpretation, therefore, resulted in smaller training sets rather than inaccurate identification. Two general problems, clouds or haze and improper film exposure, were occasionally encountered, but did not seriously affect the photointerpretation process.

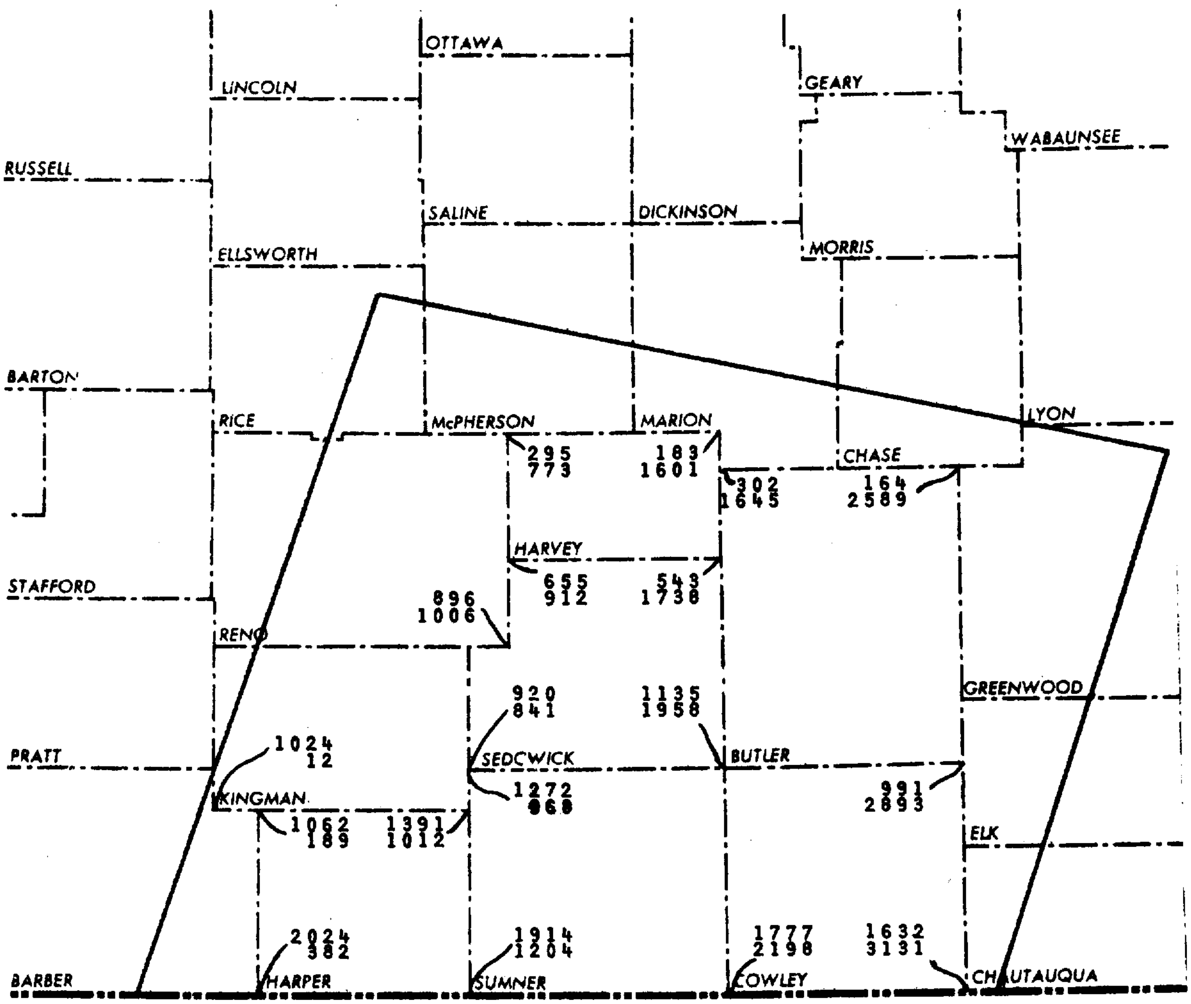
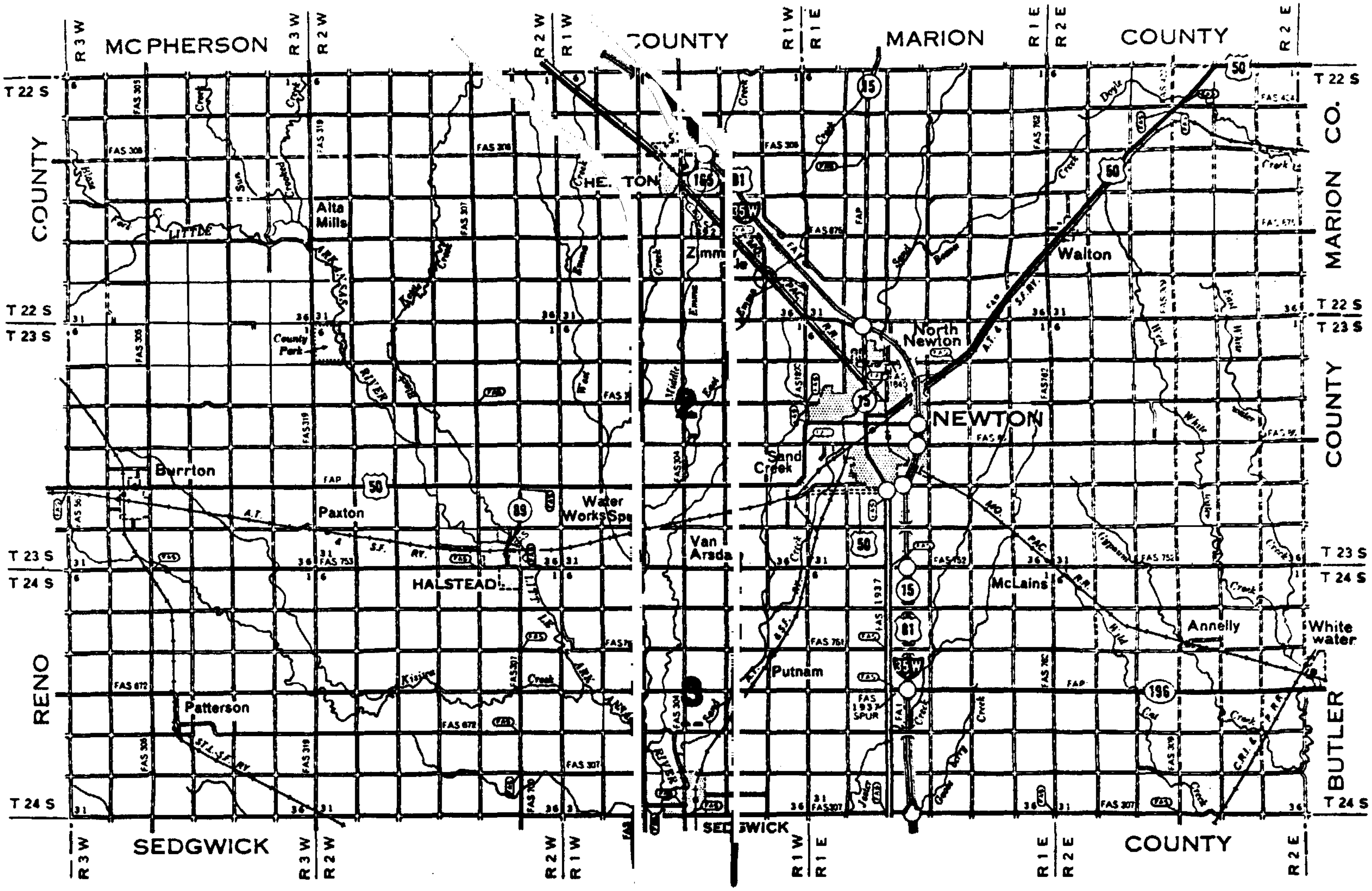


Figure 8. Example of Landsat coordinates of county boundaries.



1 = (237,1202)

2 = (402,1250)

3 = (539,1297)

Figure 9. County map showing aerial flightline and Landsat coordinates of points along it (Harvey County, Kansas).

Examples of the aerial photography over Kansas and Indiana are shown in Figures 10 and 11, respectively. These figures illustrate scale, quality, and appearance of major cover types. The difference in the number and size of fields in a section of land in the two states is also illustrated.

4.4.1 Kansas Wheat

Photography acquired on April 30, 1975, was used as reference data for all of Kansas except the Southeast CRD. On this date the wheat fields had nearly total ground cover and were light green compared to alfalfa or clover and wheat during May. Clover and alfalfa were the only other crops achieving full ground cover and a bright green color at this time in the season. Confusion of wheat with these crops was occasionally a problem, but generally clover and alfalfa were brighter red on the color infrared film and could be discriminated from wheat. The planting patterns in wheat fields also helped in its identification. Pastures could usually be easily separated from wheat fields in the infrared photography. Color infrared photography was used exclusively for this date.

Photography of June 26-27, 1975, was used for a limited area in the southeast part of the state. By this date, winter wheat was mature and harvest was ready to begin. Thus, with the straw dead, the wheat fields are golden yellow, a color which readily separates them from any other major feature present at this time. Primarily the Ektachrome color positive

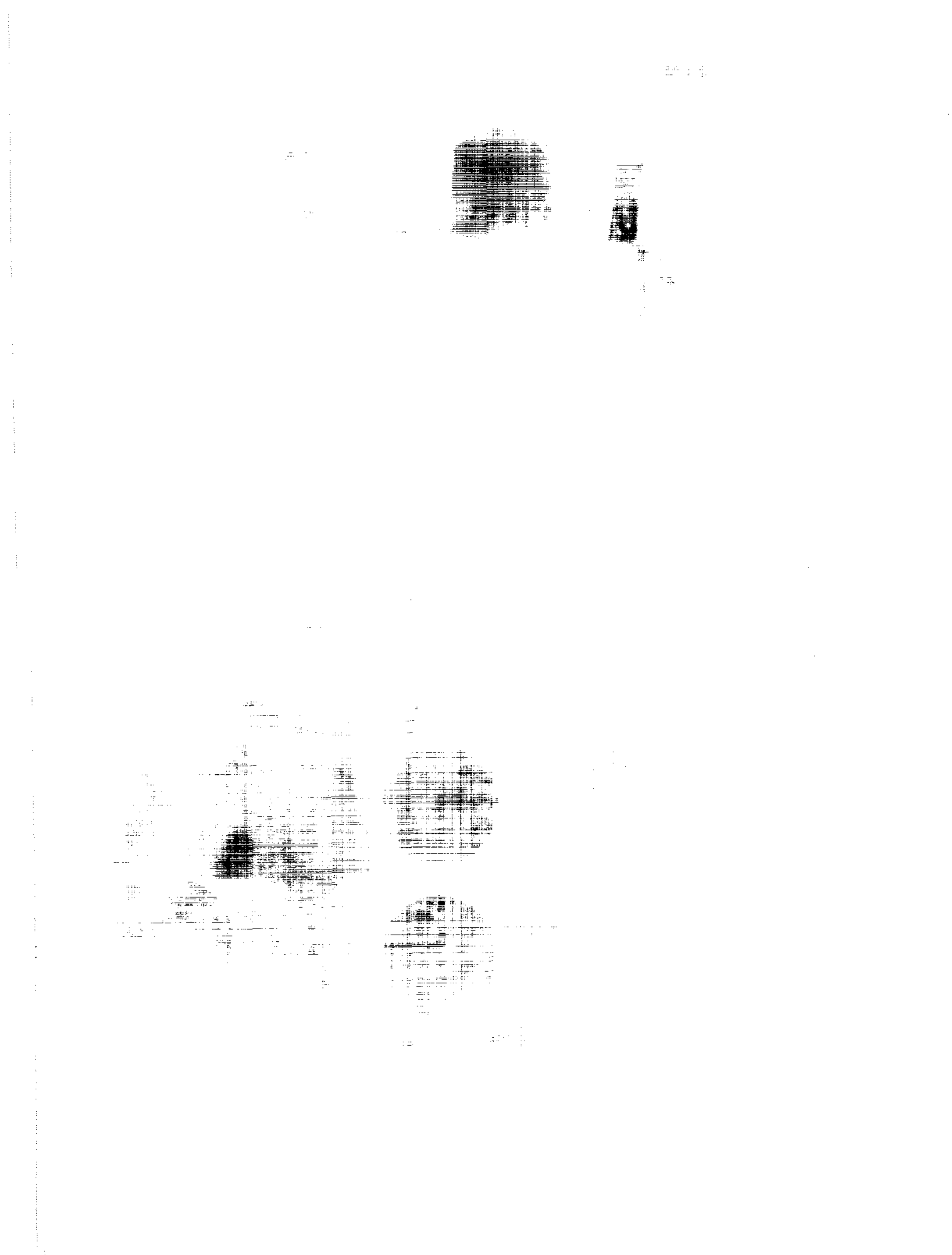


Figure 10. Examples of color infrared and color aerial photography acquired over Finney County, Kansas on April 20 and June 27, 1975, respectively.

Figure 11. Example of color infrared photography acquired over Wayne County, Indiana on August 20, 1975.

images were used for the interpretation at this date, since the wheat fields could be easily identified on it.

4.4.2 Indiana Corn and Soybeans

Almost complete coverage of the Indiana flightlines was achieved on May 27, 1975, but corn had not yet emerged and soybeans may not even have been planted at this time. Photography from this date, however, was useful in separating corn and soybean fields from other fields since corn and soybeans are the primary crops appearing as bare soil at this time.

The quality of the photography taken in July over Indiana was generally poor; there was a hazy overcast and the film was often overexposed. On the infrared film, corn fields appeared deep red and were confused with pasture. This photography was used only in conjunction with photography from another date.

During the period from August 20 to September 6, 1975, corn fields are tasseled, thus their green color as viewed from the air is not as intense. These fields are therefore easily separated from the soybean fields, which are at a full leaf stage, and have a uniform deep green color. Corn fields also exhibit more texture than most other cover types. This was the optimum period for obtaining photographic data over Indiana during 1975, and it was more extensively used as reference data than any of the other time periods. Only the color infrared images were used since soybean fields appeared as a bright red, and corn fields were of a less intense red or brownish color.

4.5 Analysis of Landsat Data

The Landsat data analysis techniques used in the investigation utilized the LARSYS Version 3 multispectral data analysis system. LARSYS is the software system, an integrated set of computer programs, for analyzing remote sensing data developed by Purdue/LARS during the past decade. The pattern recognition concept utilized in LARSYS represents a powerful and quantitative methodology for accommodating the multivariate nature of remote sensing data. While the LARSYS approach takes full advantage of modern computer technology for data processing, man is an indispensable part of the analysis process. Thus, the techniques are better described as "computer-assisted" rather than "automatic". The processing functions of LARSYS are shown in Figure 12. Its theoretical basis and details of the algorithm implementation are described in references [24] and [22], respectively.

In utilizing the LARSYS software for analyzing multispectral scanner data, one normally follows a procedure that involves: (1) defining a group of spectral classes (training classes); (2) specifying these to a statistical algorithm which calculates a set of defined statistical parameters; (3) utilizing the calculated statistics to "train" a pattern recognition algorithm; (4) classifying each data point within

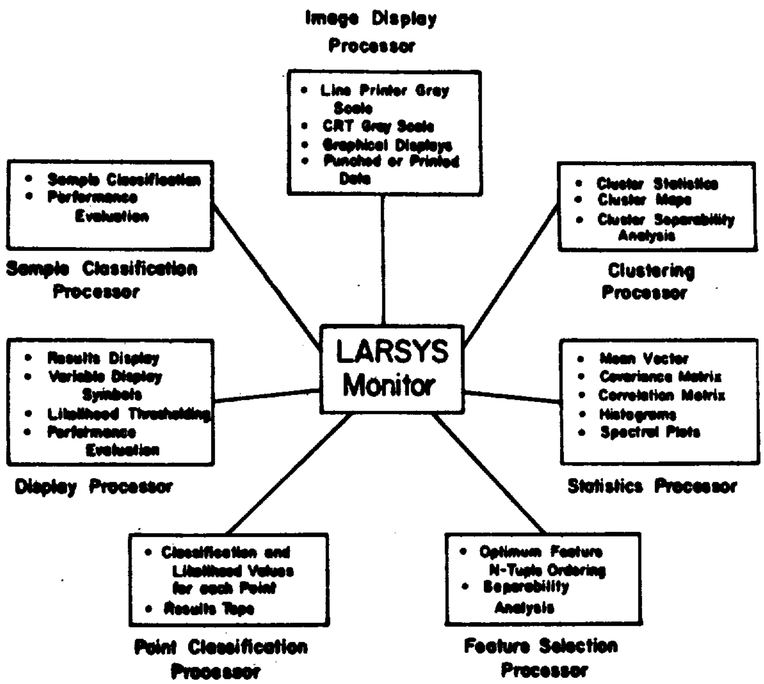


Figure 12. Analysis functions of the LARSYS software system.

the data set of interest (such as part of a Landsat frame) into one of the training classes; and finally (5) displaying the classification results in either map or tabular format (or both), according to the specifications of the application.

During the past few years, experience at LARS has shown that there are many possible refinements in the methodology utilized by the analyst for obtaining training classes, while the rest of the procedure does not vary much from one analysis task to another. The most common techniques for defining training classes involve the so-called "supervised" approach, and the "unsupervised" or "clustering" approach.

In the "supervised" approach, the analyst selects fields of known cover types and specifies these to the computer as training fields, using a system of (x,y) coordinates. The statistics are obtained for all categories of cover type in each area to be classified. The data are then classified and the results evaluated. Because the analyst had defined specific areas of known cover types to the computer, such classifications are referred to as "supervised".

The second method uses a clustering algorithm which divides the entire area of interest into a number of spectrally different classes. The number of spectral classes into which the data will be divided must be specified by the analyst. The spectral classes defined by the clustering algorithm are then used to classify the data, but at this point the analyst does not know what cover type is defined by each of the spectral classes. After the classification is completed, the analyst will identify the cover type represented by each spectral class using available reference data or cover type maps. Because the analyst does not need to define particular portions of the data for use as training fields, but must only specify to the computer the number of spectral classes into which the data is to be divided, a classification using this procedure is referred to as "unsupervised".

Additionally, several variations of these basic methods for defining training classes are possible. One is to select training areas of known cover type (a supervised approach up to this point), but then utilize the clustering algorithm to refine the data into unimodal spectral classes for each cover type. This is called a "modified supervised" approach and is the approach which was used in this investigation.

The remainder of this section describes the analysis methodology and additional details of the training procedure. An overview of the steps in the analysis sequence is shown in Figure 13.

4.5.1 Selection of Training Data

The accuracy of classification results is highly dependent upon the training data. Selection of training areas was based on two factors: first, the amount and quality of reference data (aerial photography) available, and second, the presence of a representative sample of cover types of the area(s) to be classified. To insure that the best

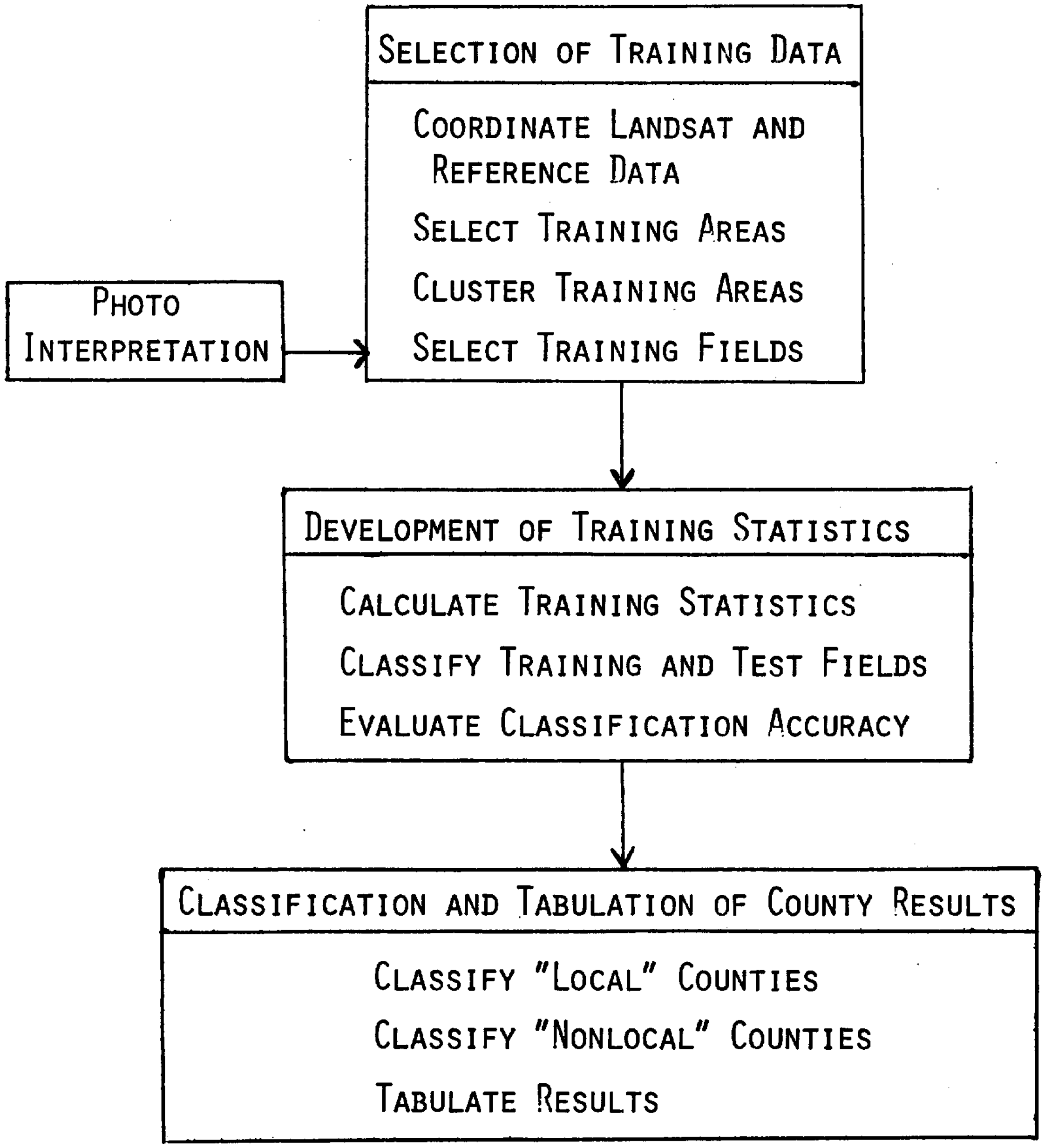


Figure 13. Flowchart of procedures used in analysis of Landsat data.

classification accuracy is obtained, a sample of every spectral class of each cover type should be included in one or more of the training areas. This provides a reasonably representative training set to the classification algorithm.

The analyst's first task was to gather and coordinate the information available about the county or counties to be analyzed. The Landsat scene had been selected (see Sec. 4.1) and the Landsat coordinates for each county boundary had been found (see Sec. 4.3). In addition, county maps had been prepared showing the Landsat coordinates of the checkpoints along the aerial photography flightline (Figure 10). The frame numbers of the aerial photography for each county were marked on the map. From this information, the analyst could determine the areas in the Landsat data corresponding to frames of aerial photography and then select the areas to be used for training the classifier.

Training areas of 100 lines and 100 columns (approximately 8 x 5.5 km) of Landsat data were selected in areas corresponding to aerial photography. For smaller counties, especially in Indiana, three to five training areas were chosen covering the entire flightline. In Kansas, four to six areas were selected with at least one in both the northern and southern portions of the county in order to adequately represent the variation present in the county.

To facilitate locating agricultural fields in the Landsat data, a spectral class map was produced by clustering each training area. The clustering algorithm implemented in LARSYS finds natural groupings in the spectral data utilizing all four wavebands. Generally six to eight classes were sufficient to provide an image on which the crop fields were readily identifiable. This approach was found to be more satisfactory than working with gray scale maps of a single spectral band.

Examples of cluster maps are shown in Figures 14 and 15; the color infrared photographs of the same areas were shown in Figures 10 and 11. The cluster maps were matched with the corresponding frames of aerial photography, and roads, towns, and field boundaries were sketched on the cluster maps.

Fields were marked on the cluster maps and their cover type identified from the aerial photography. During the photointerpretation process, the analyst became familiar with the variation in wheat, corn, soybeans, and other fields.

Training fields had to meet three criteria. First, the cover type of the fields selected for training had to be positively identified by the photo-interpreter. Secondly, the fields themselves must be of only one cover type; for example, if a ditch ran through the field, the analyst would avoid the ditch and select samples on either side of it. Thirdly, the training fields must adequately represent the variation present in the cover types throughout the area to be classified; to insure this, the fields were geographically dispersed throughout the flightline. The Landsat coordinates

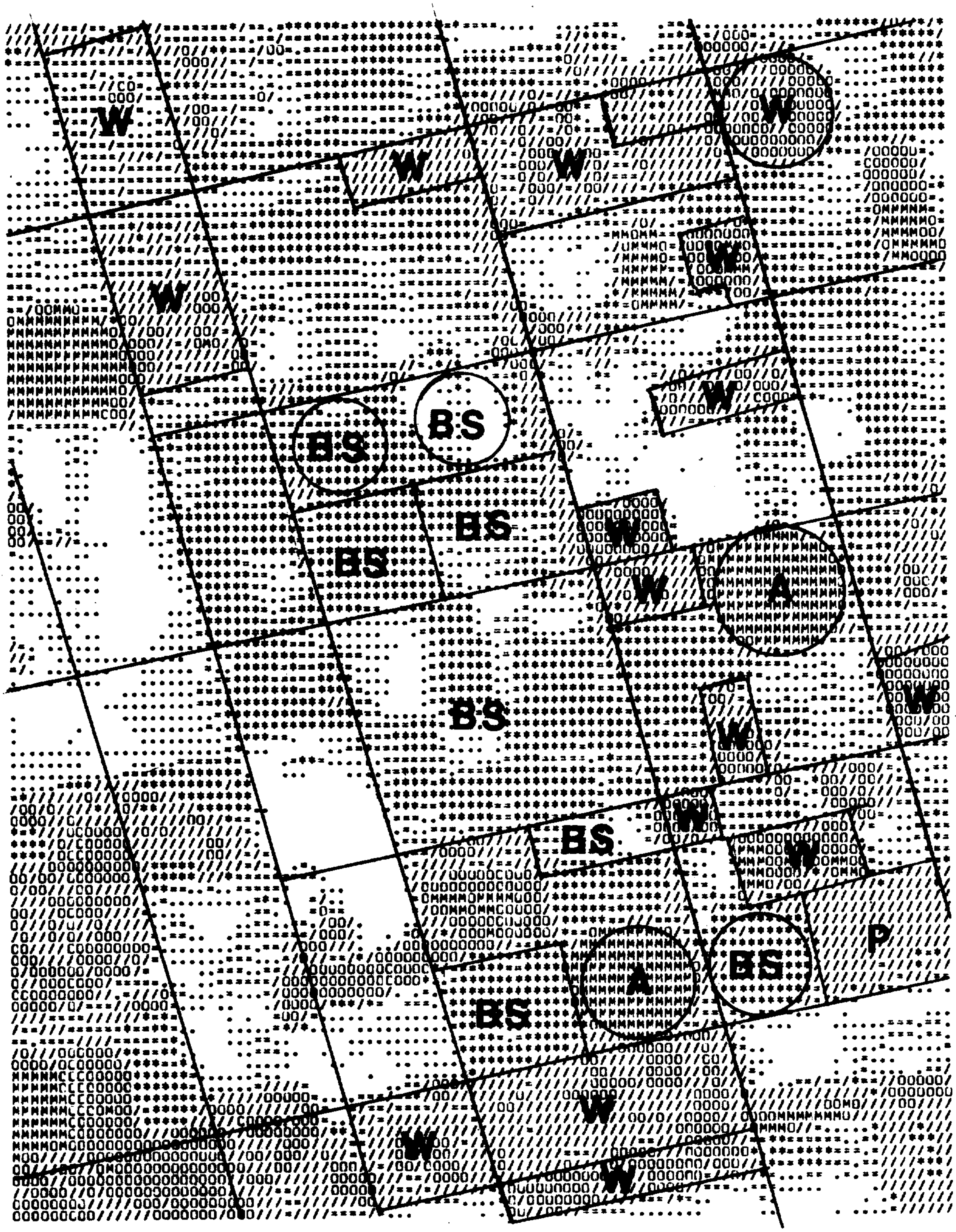


Figure 14. Example of cluster map used for location and identification of fields in Finney County, Kansas. (W = wheat, A = alfalfa, BS = bare soil, P = pasture)

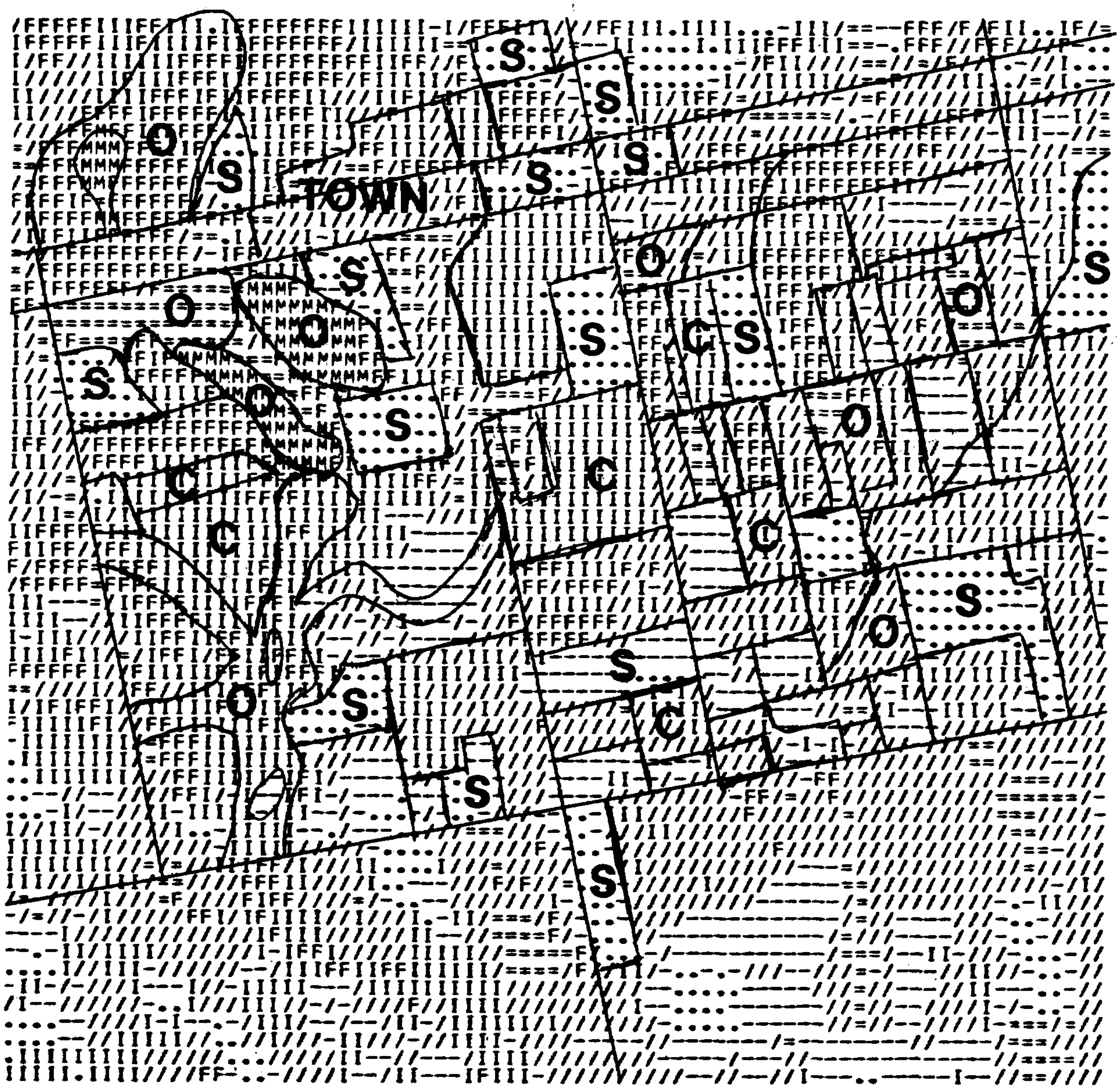


Figure 15. Example of cluster map used for location and identification of fields in Wayne County, Indiana. (C = corn, S = soybeans, O = other)

of field center (non-boundary) pixels were then obtained and field description cards prepared.

If there were any reservoirs or rivers in the county, training samples were obtained for water. If there were no bodies of water in the flightline, the analyst obtained an additional cluster map which would include water bodies. Training samples for water were then selected from this area.

As a general rule at least 25 wheat samples and 25 other samples were chosen in Kansas. In Indiana, fields were much smaller and homogeneous samples were difficult to find due to the large proportion of boundary pixels. In general, more than 25 samples each of corn, soybeans, and other were chosen, but the samples were small compared to those for Kansas.

The number of samples used for training the classifier in Kansas and Indiana is shown in Tables 6 and 7, respectively. The median number of fields used for training in Kansas was 66 and the median number of pixels used was 2600. In Indiana, the corresponding figures are 163 fields and 2750 pixels.

4.5.2 Development of Training Statistics

The training fields for each major cover type have been selected, but the spectral characteristics of each class have not been calculated. Each major cover type must be divided into its spectral subclasses, each of which must be a unimodal distribution to satisfy the assumptions of the maximum likelihood Gaussian classifier and is characterized by its mean vector and covariance matrix. Confusion between the

Table 6. Number of fields and pixels used for training and testing the classifier in Kansas.

County	Training Samples No. Fields	Training Samples No. Pixels	Test Samples No. Fields	Test Samples No. Pixels
Northwest District				
Cheyenne	47	1587		
Graham	59	1225		
Norton	30	600		
Sherman	76	2609	75	2289
West Central District				
Greeley	82	3090	81	2672
Ness	82	2400		
Trego	50	2955	51	2345
Wallace	67	4139		
Southwest District				
Finney	127	2917		
Ford	119	3320	121	2763
Hamilton	117	7161	96	5785
Haskell	77	2118		
Hodgeman	82	5105	83	4927
Seward	43	1001		
Stanton	98	6337	132	2884
North Central District				
Cloud	77	1174		
Osborne	39	1446		
Ottawa	56	3215		
Smith	97	2924		
Central District				
Barton	55	2928		
McPherson	57	2562		
Russell	42	1257		
Saline	50	1847	41	994
South Central District				
Barber	58	1942	25	2147
Harvey	69	2202		
Pratt	69	2850	71	3433
Stafford	62	2586	31	2522
Sumner	49	2244		
Southeast District				
Allen-Neosho	126	4225	131	4149

Table 7. Number of fields and pixels used for training the classifier in Indiana.

County	Training Samples No. Fields	No. Pixels
Northwest District		
Benton	144	3271
Lake	163	3424
LaPorte	167	3976
Newton	145	2684
Pulaski-Starke	192	4475
White	224	3002
West Central District		
Fountain-Parke	337	4419
Montgomery	223	3715
Owen	82	1595
Tippecanoe	92	1685
Vigo	120	2543
Warren	63	1269
Central District		
Decatur	155	2748
Grant	163	1690
Hamilton-Howard-Tipton	284	4145
Johnson-Shelby	174	2825
Madison	158	1888
East Central District		
Fayette	110	1868
Jay	166	1862
Randolph	277	3035
Wayne	203	2617

spectral subclasses of different cover types must be minimized to decrease the error in classification. The adequacy of the training statistics should be evaluated before carrying out large area classifications.

In order to satisfy the first of these three requirements, the cluster function was again used to obtain subclasses for the major cover types of wheat and nonwheat in Kansas and corn, soybeans, and other in Indiana. This time, instead of one large rectangular area, the field center samples of each of the major cover types were clustered separately to find natural groupings or spectral classes within the cover types.

Statistics were calculated to represent each spectral class and the transformed divergence between each pair of classes was calculated. The saturating transformed divergence, a number between 0 and 2000, provides a measure of the distance between classes in multi-dimensional space. High values indicate class pairs which are more separable and which, if grouped, would yield a bimodal distribution. Class pairs with small divergence values are spectrally similar and may be confused with each other during classification. If classes of different cover types were spectrally similar, the analyst inspected the fields involved by checking the location and type of field on both the cluster map and the aerial photography. If an error in field identification or location had been made, the class in error was deleted. If no error occurred, the confusion classes were left in the training statistics since deleting one or both of them would have biased the classification results.

Test field classification results, if available, or training field results were used to evaluate the adequacy of the training statistics before the county was classified in order to allow for additional training if required. For many counties in Kansas, there were enough sample fields available that both a training and a test set could be developed. A statistical test showed that the proportion estimates calculated using training field performance matrices were not significantly different in accuracy from estimates calculated using test field performance matrices. In Indiana, where the field sizes were small compared to Kansas, the number of usable samples was much smaller, and selecting test fields from the sample fields would have greatly reduced the size of the training set.

4.5.3 Classification and Tabulation of County Results

The final training statistics were used to classify a systematic random sample of the Landsat pixels within each county (Figure 16). In a systematic random sample, the first sample is chosen randomly and the remainder are determined by a constant sampling interval. Systematic random sampling was convenient and has the advantages of high precision and excellent geographic stratification [9].

For about 60 counties in Kansas and a few in Indiana, every other line and column was classified, a one-fourth

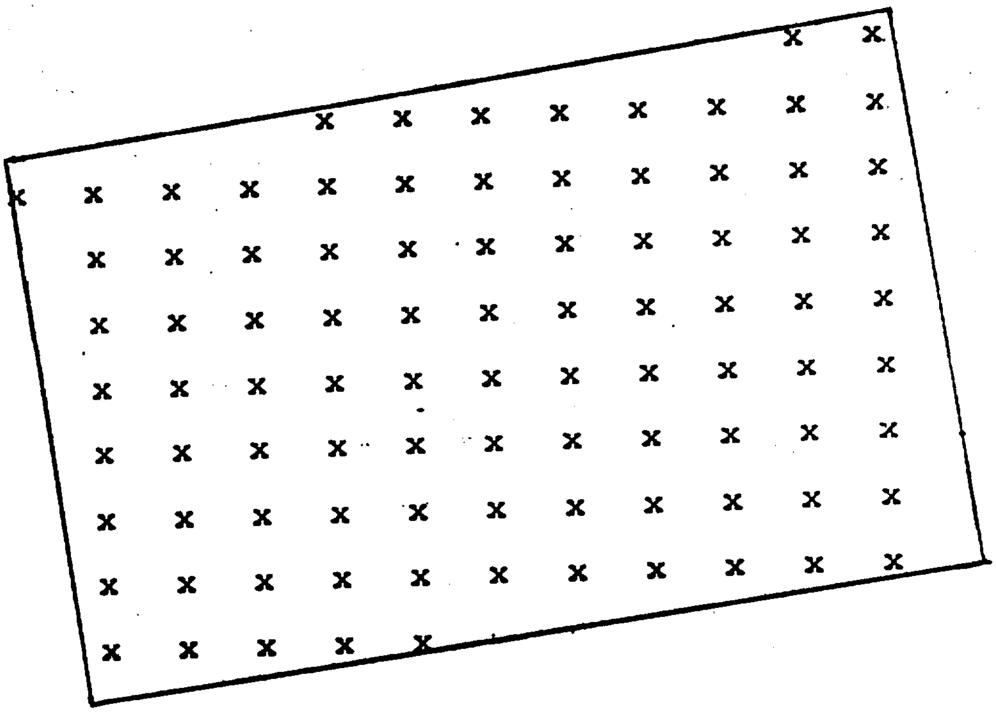


Figure 16. Schematic of a systematic random sample of Landsat pixels classified within a county boundary.

sample. However, every fourth line and column, a one-sixteenth sample, was used for the remainder of the counties. Tests showed that there was no significant difference in results obtained between these two sample sizes.

When a county was classified with a training set at least partially trained with fields from that county, the classification is labelled "local". A "nonlocal" classification is one in which the training set does not contain any training fields from the county classified. The training set used to perform a nonlocal classification came from a county in the same Landsat frame having similar soils and land use. Figure 17 is a map of Kansas showing geographically the local and nonlocal classifications and the source of training data for nonlocal classifications. Similar information for the counties classified in Indiana is given in Figure 18. Tables A1 and A2 in the appendix summarize the Landsat frame, date of data, and source of training statistics for all counties classified in Kansas and Indiana.

The number of points of each major cover type and the total number of points in the county were tabulated. These points fall within an irregular polygon in the Landsat data which corresponds to the county boundaries. Using the coordinates of cities and large towns which had been obtained earlier, the number of points of each major cover type in the urban areas were tabulated and subtracted from the county totals. These adjusted totals form the base of the area and

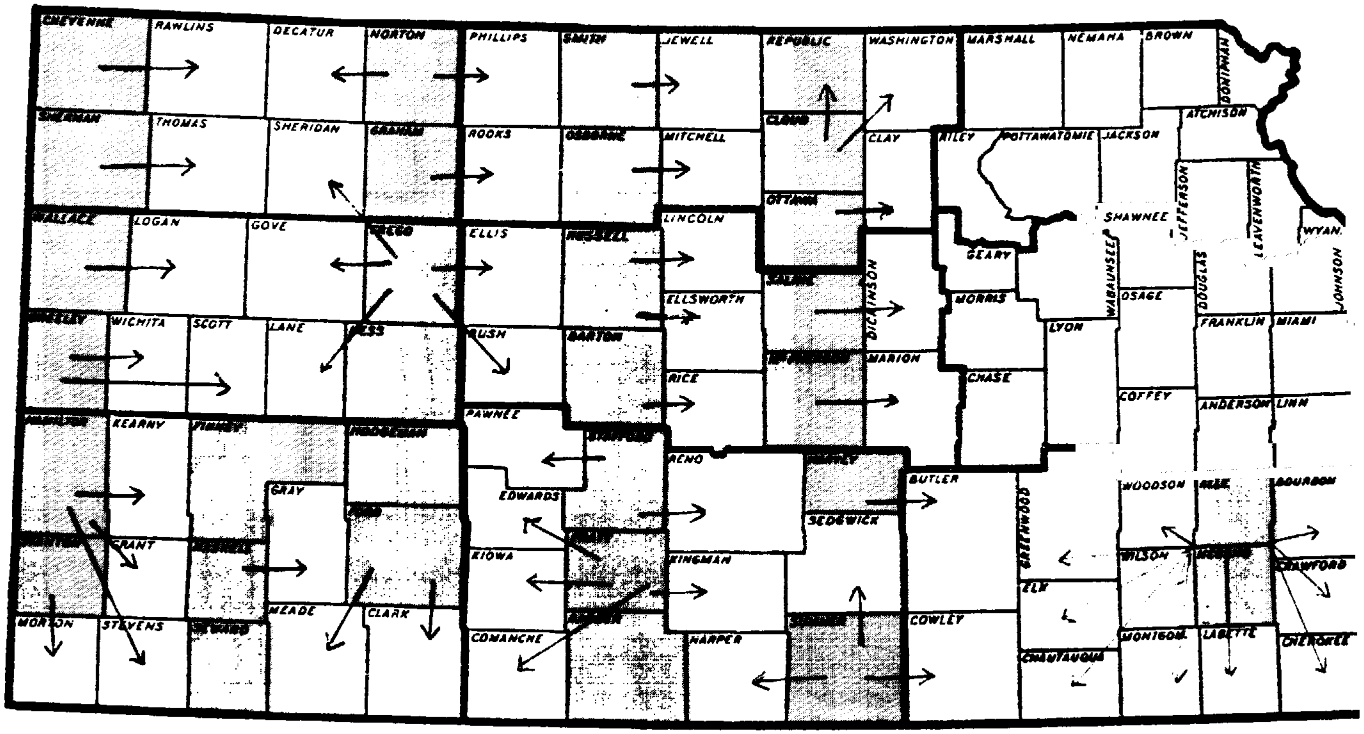


Figure 17. Local and nonlocal classifications in Kansas. Arrows point from the source of training statistics to the area classified; shaded areas denote local recognition counties.

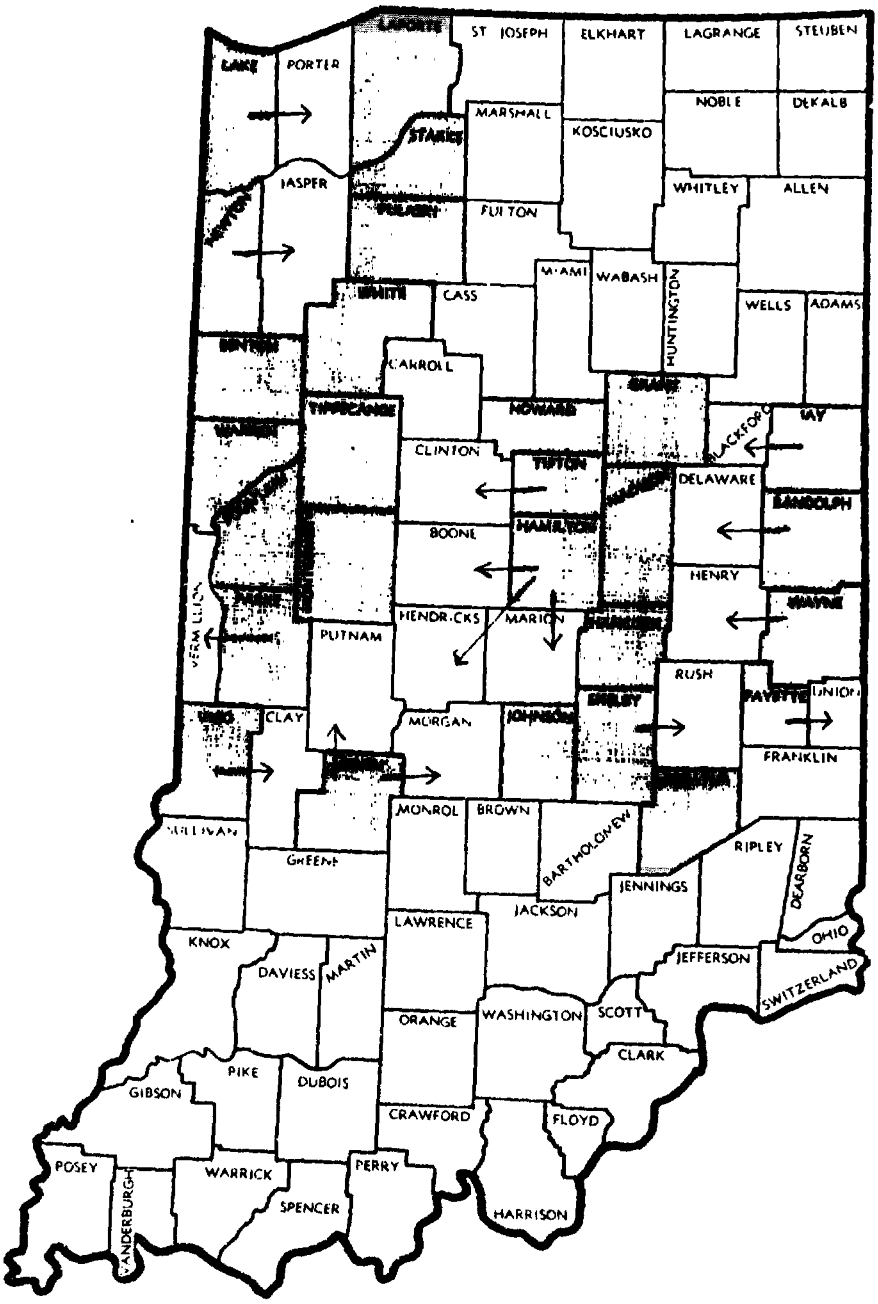


Figure 18. Local and nonlocal classifications in Indiana. Arrows point from the source of training statistics to the area classified; shaded areas denote local recognition counties.

proportion estimates for the county.

4.6 Preparation of Area and Variance Estimates

Following classification, crop area and proportion estimates were made. Estimates of the areal extent or proportion of a cover type were desired for county, crop reporting district, and state levels. The county was the smallest unit for which an estimate was wanted, so estimates of the cover types of interest were made for each county and then aggregated to the district and state levels. Steps in the area estimation procedure included: (1) calculation of the area and proportion estimates, (2) correction of the estimates for classification bias, and (3) calculation of variance estimates. For counties in which Landsat classifications were not performed, a regression procedure utilizing historical data and current Landsat estimates was used.

4.6.1 Area and Proportion Estimates

The Landsat estimated proportion of the $i^{\underline{th}}$ crop in the $j^{\underline{th}}$ county was calculated using the equation

$$\hat{p}_{ij} = \frac{n_{ij}}{n_j}$$

where n_{ij} is the number of pixels classified as crop i and n_j is the total number of pixels in the sample. The estimated hectares of crop i in the $j^{\underline{th}}$ county can be calculated in two equivalent ways:

$$\hat{h}_{ij} = \hat{p}_{ij} h_j$$

where $\hat{p}_{ij}$ is defined as above and h_j is the number of hectares in the county, or

nonsense

$$\hat{h}_{ij} = k\, n_{ij} \qquad k N_j \cdot \frac{n_{ij}}{n_j} \qquad N_j = \text{\# pixels in county } j$$

where n_{ij} is as above and k is the area in hectares of a pixel (approximately 0.45).

Area and proportion estimates for the crop reporting districts and the entire state are aggregated from the county estimates. The area estimate of crop i for a CRD is found by $\Sigma\, \hat{h}_{ij}$, summing the area estimates from all the counties in the CRD. The proportion of crop i in a CRD is found by $\frac{\Sigma \hat{h}_{ij}}{\Sigma h_j}$ where the summations are taken over all the counties in the CRD and $\hat{h}_{ij}$ and h_j are as defined above. Area and proportion estimates for entire states are found similarly.

4.6.2 Correction for Classification Bias

Experience has shown that it is inevitable that some pixels are incorrectly identified by the maximum likelihood classifier. The primary source of these errors is overlapping density functions for two or more classes. For example, some corn looks like soybeans and/or some soybeans are spectrally similar to corn. Classification errors of this type cause the resulting area estimates to be biased. However, if the error rates are known the area estimates can be adjusted or unbiased after the classification has been performed. This technique was first used in the 1971 Corn Blight Watch

Experiment [18] and later in a Landsat-1 investigation by LARS [4].

An estimate of the classification error rates is the matrix of training or test field classification performance,

$$E = \begin{pmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{pmatrix}$$

where e_{ij} is the proportion of samples of type i classified as type j. If P is the vector of true proportions of the cover types and $\hat{P}$ the proportions estimated from the Landsat data, then

$$\overset{\text{random variable}}{\hat{P}} \overset{\circ}{=} \overset{\text{constant}}{E^t P}.$$

Since $\hat{P}$ and E are known from the classification, but P, the vector of true proportions, is not known,

$$P = \left(E^t\right)^{-1} \hat{P}$$

is solved. The example of Figure 19 shows how this is done.

It is possible for this method to give a negative value for the proportion of a cover type. Since it is unrealistic for an estimate of a proportion or probability to be negative, an alternative problem was considered when this occurred:

$$\min_{0 \le p_i \le 1} \left\| P - \left(E^t\right)^{-1} \hat{P} \right\|$$

for all p_i, elements of the vector P. This is equivalent to minimizing the Euclidean distance (denoted by $\| \cdot \|$) between the true proportion and the Landsat corrected estimate. The vector of proportion estimates after bias correction is

$$E = \begin{pmatrix} .85 & .15 \\ .18 & .82 \end{pmatrix}$$

$$E^T = \begin{pmatrix} .85 & .18 \\ .15 & .82 \end{pmatrix}$$

$$(E^T)^{-1} = \begin{pmatrix} 1.2239 & -.2687 \\ -.2239 & 1.2687 \end{pmatrix}$$

$$\hat{P} = \begin{pmatrix} 38.9 \\ 61.1 \end{pmatrix}$$

$$P = \begin{pmatrix} 1.2239 & -.2687 \\ -.2239 & 1.2687 \end{pmatrix} \begin{pmatrix} 38.9 \\ 61.1 \end{pmatrix} = \begin{pmatrix} 31.2 \\ 68.8 \end{pmatrix}$$

SRS HARVESTED	LANDSAT UNCORRECTED	LANDSAT CORRECTED
31.6	38.9	31.2

Figure 19. A numerical example of classification bias correction (Cloud County, Kansas).

denoted by $\hat{\hat{P}}$. The discussion of bias correction generalizes to n cover types of interest with E being an n x n matrix and the vectors having n components.

The corrected estimate will be unbiased if the error matrix found from the test or training field performance is the true error matrix. It may not be truly unbiased because of photointerpretation difficulties or because the flightline might not be representative of the entire area classified.

4.6.3 Calculation of Variance Estimates

In addition to knowing the accuracy of an estimate, it is desirable to know the precision, or variance, of the estimate. The variances of the proportion and area estimates were obtained as follows. Since each pixel is classified as crop i or not, the binomial distribution can be used to obtain the variance of the bias-corrected proportion estimates. For the $j^{\underline{th}}$ county, an estimate of the variance is given by

$$v\left(\hat{\hat{p}}_{ij}\right) = \frac{\hat{\hat{p}}_{ij}\left(1-\hat{\hat{p}}_{ij}\right)}{\left(n_j-1\right)}\left(1-f_j\right)$$

where f_j is the county sampling fraction [8]. For individual county estimates, the sampling fraction can be ignored (though it is not negligible) to give a conservative estimate of the variance. As

$$\hat{\hat{h}}_{ij} = \hat{\hat{p}}_{ij}\, h_j$$

the variance of the area estimate $\hat{\hat{h}}_{ij}$ can be calculated by

$$v\left(\hat{\hat{h}}_{ij}\right) = h_j^{\,2} \; v\left(\hat{\hat{p}}_{ij}\right)$$

where h_j is the total number of hectares in the county.

In calculating the proportion estimate from the sample the assumption is made that each pixel would be classified as a particular crop or not classified as that crop, which leads to a multinomial or binomial model of the classified data. The binomial distribution can be used to estimate the total number of wheat pixels and the percentage of wheat in the area. Theoretical estimates of the sampling error are then available [8]. It is also assumed that there is no cyclic pattern in the data to bias the estimate from a sample taken systematically. To test these assumptions, a sampling study was performed early in this project.

The study examined the sampling error produced for a given sampling fraction against the theoretical error given by using binomial distribution theory. In order to measure just the effect of sampling, the error introduced in classification was ignored by comparing the various samples to a 100% sample. The results are based on classifications of Rice and Morton Counties, Kansas, and were substantiated by further tests in Benton and Wayne Counties, Indiana.

In the Kansas sampling study, estimates of both the total number of wheat resolution elements and the percentage of wheat in the area were calculated for sampling fractions of 50, 33.3, 25, 11.1, 10, 6.25, 4, and 2.8 percent. These samples were taken systematically. For example, an 11.1% sample of the area was obtained by tabulating the classification with both a line and column interval of three. Nine 11.1% samples were selected with a different starting point for each sample. The theoretical variance of these sample estimates was calculated from the binomial distribution and compared to the variance among the repeated estimates of the same sample size. For example, the theoretical variance of an 11.1% sample was calculated and then compared to the variance of the nine sample estimates.

The results of the study (Table 8) showed that in all cases the two variances were not significantly different, indicating that the theoretical estimate of the sampling error based on the binomial distribution can be used as the estimate of the variance of the proportion estimate. The Morton results show a cyclic effect due to "six line scan" noise. In practice, Landsat data with such a noise problem was avoided. Wayne and Benton Counties in Indiana were used to test the applicability of the Kansas results to Indiana. The results were consistent with those of Kansas.

rather subjective — look quite different in some cases

The variance for a crop reporting district can be obtained in two ways. The variance can be calculated as though a systematic random sample were taken throughout the district or it can be calculated considering each county as a stratum. The estimated variance for crop i in the stratified case would be given by:

Table 8. Theoretical and computed sampling errors of wheat proportion estimates for different sample sizes in two counties in Kansas.

	Standard Error (%)	
% Sample	Theoretical	Computed
Rice County		
50.0	0.0902	0.0361, 0.1126*
33.3	0.1277	0.1018, 0.1597
25.0	0.1563	0.0992
11.1	0.2555	0.1824
10.0	0.2717	0.1752, 0.1937
6.25	0.3509	0.2812
4.0	0.4453	0.2797
2.8	0.5358	0.4890
Morton County		
50.0	0.0867	0.1293, 0.9233
33.3	0.1226	0.0430, 1.0067
25.0	0.1501	0.7637
11.1	0.2455	0.8799
10.0	0.2599	0.3358, 0.6939
6.25	0.3372	0.6948
4.0	0.4241	0.3405
2.8	0.5152	2.6950

* 50.0%, 33.3% and 10% systematic samples can be taken in two ways. For example, a 50% sample can be either every other line or every other column.

$$\Sigma W_j^2 \frac{\hat{\hat{p}}_{ij}\left(1-\hat{\hat{p}}_{ij}\right)}{n_j}\left(1-f_j\right)$$

where the summation is taken over all counties in the crop reporting district [8].

In essence, it matters little what formula is used to calculate the variance estimates whether conservative or not, because the estimates are very small in either case. The distribution in Indiana is actually given by the multinomial, but the variances can be calculated by considering each crop separately with the binomial assumptions.

4.6.4 Estimation for Counties Without Landsat Data

An alternative approach for crop estimation must be taken when adequate data for Landsat classification is not available for an area. One approach to this problem lies in formulating a regression equation from which a crop prediction can be made.

Regression is valid as a predictor only for the population from which it is derived. This predictor will not be valid for a county which has historical crop acreage or county size falling outside the range of values used in the derivation of the regression equation. For these counties, the 1974 USDA/SRS area estimates were used as the 1975 estimates. Revised estimates from Kansas and preliminary estimates from Indiana were used.

For Kansas, the regression model used to predict the area in hectares of wheat in a given county was:

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$

where x_1 is the 1974 USDA/SRS wheat acreage for the county, x_2 is the 1973 USDA/SRS wheat acreage for the county, and x_3 is the total number of acres in the county. The coefficients β_0, β_1, β_2, and β_3 are estimated by using the available Landsat estimates as y values. A pseudo-Landsat estimate is made by applying these coefficients to the x values of the counties to be estimated.

Only historical data could be used in the regression in order to simulate real-time estimation. It was felt that wheat data before 1973 should not be considered because major increases in the wheat acreage planted occurred beginning in 1973. The area of the county was also included as a factor which might contribute to the amount of wheat grown.

For Indiana, similar regression models were used to predict the area in corn and soybeans. Again, the variables considered as predictors were the number of acres in the county and the USDA/SRS estimates of acres harvested in 1973 and 1974 for corn or soybeans. The regression model used was:

$$\hat{y}_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_3$$

where $\hat{y}_i$ denotes the area in hectares of crop i, x_{1i} is the 1974 USDA/SRS estimate of acreage in crop i for the county, x_{2i} is the 1973 USDA/SRS estimate of acreage in crop i in the county, and x_3 is the total number of acres in the county.

4.7 Evaluation of Results

Once an adequate training set has been defined, it is not difficult to classify large geographic areas using computer analysis techniques. However, unless the accuracy of such computer classification results can be verified, little has been accomplished by simply classifying the data over various areas of interest.

In this investigation two quantitative evaluation techniques were used to judge the accuracy of crop classifications and area estimates. One evaluation involved statistical sampling of individual areas of known cover types (designated as test fields). This offers an effective method of examining inclusive and exclusive classification errors for the various crops or cover types. Such techniques, however, must be used with caution, and must be carefully designed to provide statistical reliability of the results. In general, areas need to be selected in such a way that the number of resolution elements in the test areas for each cover type are approximately in proportion to the amount of that cover type present in the area.

A second quantitative technique for evaluating classification accuracy is comparison of area estimates from the computer classification and area estimates obtained by some conventional method. Ideally, crop area measurements from large contiguous areas would be used for comparison.

Realistically, it is not possible to acquire a large amount of such data. Therefore estimates of the crop areas or proportions must be used. The USDA/SRS annually publishes estimates of the acreage of major crops for counties, districts, and states. Estimates or measurements for a smaller unit such as a township are generally not available.

In addition to evaluating the classification accuracy, several factors which might have affected accuracy were examined.

4.7.1 Assessment of Training and Test Field Classification Accuracy

Test fields are frequently used to evaluate the accuracy of the Landsat classifications. Areas with a known cover type which were not used for training are chosen as test fields. These are then classified and the accuracy of the classifier determined by the proportions of pixels which are correctly identified. If these fields have been randomly selected and their classification accuracy is high, then the classification of the entire area should be accurate.

In this project test fields were chosen in a manner similar to training fields. Some of the fields identified from the aerial infrared photography were randomly selected as test fields. The method of random selection depended upon the analyst and included systematic sampling, stratified random sampling, and simple random sampling. However, in some counties all the available fields were used for training, leaving none for test. In these cases, training field performance was evaluated to determine the accuracy of the classifier, since a statistical test of counties with both test and training fields showed that using training fields to evaluate classification accuracy was not significantly different from using test fields.

4.7.2 Statistical Comparison of Landsat and USDA/SRS Estimates

The standard of comparison for Landsat estimates was the USDA/SRS estimate of acres harvested. SRS estimates were used primarily because of their availability on a state, crop reporting district, and county basis for 1975. There is a national agricultural census which also provides these estimates, but it is performed only every five years and was not taken in 1975. Acres harvested were used rather than acres seeded because:(1) the acquisition of Landsat data used in this analysis was closer to harvest time than to seeding time and (2) the harvested acreages are used for estimating total production. Estimates of both the proportion of total land area and of the area in hectares of a crop were considered as variables.

The purpose of USDA/SRS crop surveys is, primarily, to make national estimates and, secondly, state estimates. The state estimates are considered to be unbiased and to have small coefficients of variation, generally not exceeding about 5% for major crops [23]. The SRS does publish county and crop reporting district estimates, but coefficients of variation are not calculated for these estimates. It is expected that the county and CRD estimates will not be as accurate as the state and national estimates, and that the coefficients of variation will be larger at the county level. The SRS county estimates then are not the ideal standards for comparison, but must be used due to lack of any more reliable data.

The method used to arrive at county estimates varies from state to state. In Indiana, county estimates are made on the basis of mail surveys. About 12,000 questionnaires are mailed to get a response of at least 4,000. This should guarantee at least 50 responses per county on which to base the estimates. The mail survey results are adjusted for the difference from the June enumerative survey (E. L. Park, State Statistician, Indiana, personal communication). Kansas, however, uses information from three different surveys to calculate county estimates. The first is the annual State Farm Census which is supposed to be an enumeration of all farming operations in the state, but which contains some incompleteness. Mail surveys from June and late summer are combined with the census data to form a composite area estimate for each county. These are then adjusted for various factors and scaled to add to the state estimate (M. E. Johnson, State Statistician, Kansas, personal communication).

The levels for testing Landsat against SRS estimates were determined according to the problem at hand. In choosing a significance level, a large α is chosen to minimize the chance of claiming the hypothesis of equality is true when it is really false; a small value of α is chosen to minimize the chance of rejecting the hypothesis of equality when it is actually true. To ascertain whether SRS and Landsat estimates were close, the two estimates were obtained and the hypothesis of their equality, the null hypothesis, was tested. Statistical tests are not designed to prove that the null hypothesis is true, although in this case that is what we did want to conclude. In order to be reasonably certain that the SRS and Landsat estimates are the same, the probability of accepting the hypothesis of equality, when it was in fact false, was made very small. This was achieved by choosing a large value of α such as 0.25.

4.7.3 Analysis of Factors Affecting Classification Accuracy

In order to perform statistical tests on the Landsat estimates, normality and homogeneity of the data must be considered. Standard tests for homogeneity were not useful here because they consider the variance of the sample variances, which in this case was zero because the variance σ^2 is determined rather than estimated by the large sample size used in Landsat estimation. Instead, the range was used to determine if the variances were homogeneous for tests on proportions.

Variances are stable only for proportion estimates in the 0.30-0.70 range [1]. Since some values of the Landsat proportion estimates fell outside this range, a transformation was required. For this range, p was transformed by arcsin $\sqrt{p}$ [1].

The nonhomogeneity of the data affects the statistical test results by introducing a bias into the test statistic, in this case either an F-statistic or a t-statistic. The bias of the F-statistic for the Kansas proportion variances was calculated and found to be 1.29 [6]. Thus, when testing a hypothesis with a significance level of $\alpha = 0.05$, the hypothesis is really being tested with $\alpha = 0.09$, and will be rejected too often. For this amount of bias, p should be transformed.

The bias of the test statistic for Kansas area estimate variances was found to be 1.17. Thus when testing a hypothesis with a significance level of $\alpha = 0.05$, the hypothesis would really be tested with $\alpha = 0.07$. This is not as biased as is the case with the proportion variances, though the null hypothesis would be rejected slightly too often. Testing was performed on these variables without transformation. With larger sample sizes, homogeneity tends to be a minimal problem. For Indiana, the proportion estimates were transformed and the hectare estimates were not, following the same pattern as for Kansas.

Numerous tests were made to identify and assess factors which might affect the accuracy of the area and proportion estimates. Those factors tested included: date of the Landsat coverage, date of the aerial photography (Indiana only), effect of the data analyst (Kansas only), the effect of local versus nonlocal recognition, and the effect of geographic location (crop reporting districts).

For Kansas, two types of tests were made for testing the effect of date. The first was a paired comparison of 10 counties which had been classified twice using two different Landsat frames. The second type of test, done in both Kansas and Indiana, used all counties which were classified and tested for a difference due to groups of dates. A limitation of this test is that date effects may be confounded with other factors such as geographic location.

Tests for the effect of aerial photography date were not done in Kansas because essentially only one date was used. For Indiana, all counties were included in the analysis and tests were performed in the same manner and with the same limitations as the tests for the effect of date of Landsat data.

In tests for the data analyst and local vs. nonlocal recognition effects, all available data were utilized. In tests to determine the accuracy of a CRD or state, duplicate observations were not permitted. Of these duplicates, the estimate derived from the Landsat pass closest to harvest was used without reference to which one was closer to the SRS estimate.

5.0 WHEAT IDENTIFICATION AND AREA ESTIMATION IN KANSAS

In this section the results of the Landsat data analysis for winter wheat identification and area estimation in Kansas are presented and evaluated. The material includes a discussion of factors affecting classification accuracy, comparisons and evaluations of training and test field classification performance, and comparisons of USDA/SRS estimates to Landsat-derived estimates of the area and proportion of wheat. Finally, the accuracy and precision of the Landsat estimates are discussed.

5.1 Analysis of Factors Affecting Classification Accuracy

Although an assessment of factors affecting classification performance was not a primary objective, several analyses to assess factors which might have influenced classification results were performed in order to more fully understand and interpret the results. The variables tested included: Landsat acquisition date, data analyst, local vs. nonlocal classifications, and the interaction of date and locality. The results of these tests are presented in this section.

5.1.1 Effect of Landsat Acquisition Date

Ten of the 13 counties in the South Central Crop Reporting District were classified twice, using data from two different Landsat passes. All counties were classified using April data and then reclassified using either May or June data (Table 9). Since these were the only counties for which multitemporal data were available, they were used to explore the effect of dates on classification performance. The "goodness" of an estimate was considered to be its closeness to the SRS estimate. Paired t-tests showed that there was no significant difference ($\alpha = 0.25$) in the accuracy due to the date of Landsat coverage. The inference of these tests is not strong due to the small sample size, so a further study on the effect of dates with larger samples was performed.

A second analysis, including all counties in the seven districts classified, was performed to determine if there was an effect due to the date of the Landsat data acquisition, ignoring other factors. Five groups of dates were considered: early April, early May, late May, mid-June, and early July. An analysis of variance showed that neither the proportion nor area estimates were significantly affected by Landsat data acquisition period. These results indicate that date was not a major factor influencing the classification performance and that all counties regardless of the date of Landsat data

Table 9. Comparison of wheat estimates from April and May or June Landsat data acquisitions to USDA/SRS harvested estimates, South Central Crop Reporting District, Kansas.

County	Date	USDA/SRS Harvested Hectares	USDA/SRS Harvested Proportion	Landsat Classification Hectares	Landsat Classification Proportion	Difference From SRS Hectares	Difference From SRS Proportion
		(000)	(%)	(000)	(%)	(000)	(%)
Barber	April	69.1	23.3	23.1	7.8	-46.0	-15.5
	May	69.1	23.3	89.4	30.1	20.3	6.8
Comanche	April	43.4	20.9	31.1	15.0	-12.3	- 5.9
	May	43.4	20.9	46.3	22.3	3.0	1.4
Edwards	April	53.1	33.4	58.0	36.4	4.9	3.1
	May	53.1	33.4	46.6	29.3	- 6.5	- 4.1
Harper	April	116.3	56.0	110.8	53.4	- 5.5	- 2.6
	June	116.3	56.0	117.8	56.8	1.5	0.7
Harvey	April	55.0	39.3	55.3	39.5	0.3	0.2
	June	55.0	39.3	42.2	30.2	-12.8	- 9.1
Kingman	April	97.0	43.3	113.7	50.8	16.7	7.5
	May	97.0	43.3	124.8	55.8	27.9	12.4
Kiowa	April	51.3	27.5	43.3	23.2	- 8.0	- 4.3
	May	51.3	27.5	45.6	24.4	- 5.6	- 3.0
Pratt	April	82.6	43.7	91.3	48.3	8.8	4.6
	May	82.6	43.7	80.5	42.6	- 2.0	- 1.1
Sedgwick	April	105.3	40.7	71.0	27.5	-34.3	-13.3
	June	105.3	40.7	117.3	45.4	12.0	4.6
Sumner	April	196.9	64.3	217.0	70.9	20.1	6.6
	June	196.9	64.3	195.8	63.9	- 1.1	- 0.4

acquisition can be considered together. The results also mean that a best date for Landsat coverage cannot be recommended from this study.

5.1.2 Effect of Data Analyst

Since there was no significant date effect, the effect of analysts on the classification performance could be considered. This was a nested design with counties appearing within analysts. Three analyses were run: (1) all counties (2) all local counties, and (3) all nonlocal counties. Each result showed that the analyst effect was nonsignificant at any reasonable α level when considering either proportion or area estimates. Since all analysts used similar methods, no inferences can be made about methodology; but it can be concluded that individual analysts did not introduce a bias in the results.

5.1.3 Effect of Local vs. Nonlocal Recognition

One of the major problems encountered in the LACIE has been to develop a means for successfully extending training statistics from a training segment to "recognition" segments. In our investigation a different methodology involving stratification of counties into groups having similar characteristics and developing training statistics from throughout the training county was used. To determine if this method was satisfactory for classifying several counties the effect of local vs. nonlocal classification was tested. For proportion estimates, the difference became apparent at the 20% significance level. For area estimates, however, the difference was significant for any α larger than 0.10. Our conclusion is that there was some difference in performance between local and nonlocal counties; the amount of wheat was overestimated in local counties and underestimated in nonlocal counties; but, on the average, nonlocal recognition counties were closer to SRS estimates than the local recognition counties. It can probably be concluded that this factor did not have a strong influence on the overall results.

5.1.4 Effect of Interaction Between Dates and Locality

In the South Central Crop Reporting District, there appeared to be an interaction between date of the Landsat coverage and locality. Since the sample size was too small to draw any inference, a plot was made to examine this effect for the entire state. The interaction that was present in the South Central district analysis was not present over the entire state, although other factors which may have affected the accuracy were ignored. There is no good test on the significance of this interaction since variance estimates from the SRS are not available.

5.2 Landsat Classification Results

The Landsat classification results include the training and test field performances; estimates of the area and proportion of wheat for the state, districts, and counties; comparisons of the Landsat estimates to USDA/SRS estimates; and evaluation of the accuracy and precision of the Landsat estimates. In addition regression estimates of wheat area and proportion in two districts for which Landsat data was not available are presented.

5.2.1 Classification Accuracy

Classification accuracy was determined by the test field or training field performance matrices. The training field classification performance for all local recognition counties is given in Table 10. The test field performance is given in Table 11 for those counties which had test fields. The accuracy of the classification as assessed by training fields is not significantly different from that found by measuring test field performance. The overall classification performances are generally 85% or higher, an indication that the classification should result in accurate area estimates.

Since the classification performance of test (or training) fields was used to correct for classification bias in the area estimates, a plot was made of the absolute value of the bias correction of the Landsat results and the overall classification accuracy to show the relation between them (Figure 20). The simple correlation between these two variables is $r = -0.80$. The amount the Landsat estimates were adjusted

Table 10. Classification accuracy of training fields in Kansas.

	CLASSIFICATION	ACCURACY (%)	
COUNTY	WHEAT	OTHER	OVERALL
CHEYENNE	87.8	99.0	91.8
GRAHAM	84.3	87.2	86.1
NORTON	93.7	87.0	89.5
SHERMAN	70.3	97.5	89.5
CLOUD	85.1	81.9	83.0
OSBORNE	95.4	98.6	97.4
OTTAWA	99.3	99.5	99.3
SMITH	88.3	87.0	87.2
GREELEY	82.7	93.8	90.0
NESS	95.7	89.8	91.3
TREGO	76.8	77.1	77.1
WALLACE	51.7	97.7	90.0
BARTON	95.3	83.7	87.8
MCPHERSON	99.5	98.8	99.1
RUSSELL	95.0	92.2	93.5
SALINE	72.3	92.7	82.5
FINNEY	97.0	94.5	95.4
FORD	94.9	98.8	97.4
HAMILTON	75.3	55.5	61.9
HASKELL	96.4	98.8	97.8
HODGEMAN	86.3	79.3	81.3
SEWARD	97.8	98.2	98.0
STANTON	66.8	62.9	63.6
BARBER	96.3	99.7	98.1
HARVEY	98.1	93.7	95.5
PRATT	99.8	94.8	97.0
STAFFORD	94.4	98.5	96.4
SUMNER	93.4	95.3	94.3
ALLEN	94.2	94.5	94.4

Table 11. Classification accuracy of test fields in Kansas.

COUNTY	CLASSIFICATION ACCURACY (%) WHEAT	OTHER	OVERALL
SHERMAN	75.4	89.0	85.0
GREELEY	84.8	93.0	89.9
TREGO	86.7	81.1	82.4
SALINE	83.5	94.5	87.5
FORD	93.7	97.0	95.7
HAMILTON	94.2	78.4	82.5
HODGEMAN	89.4	77.7	80.9
STANTON	62.5	79.1	75.5
BARBER	92.7	88.8	90.4
HARVEY	93.6	98.2	95.6
PRATT	92.7	95.6	93.8
STAFFORD	99.5	93.4	96.0
SUMNER	92.6	89.2	91.2
ALLEN	95.3	89.7	90.7

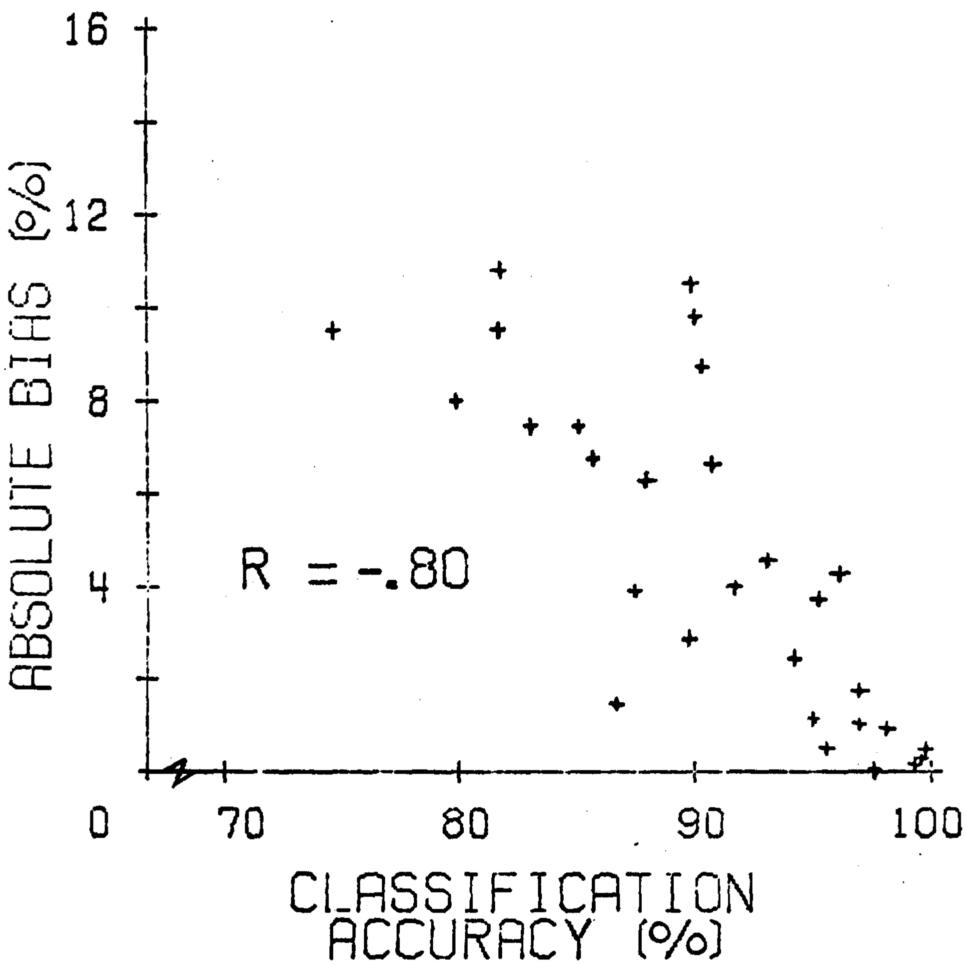


Figure 20. The relationship of the magnitude of the calculated bias correction to overall classification accuracy.

depends primarily upon the classification accuracy, but also on the estimated proportion of wheat in the county. The graph clearly shows that high classification performance is desirable to reduce the need for classification bias correction. High classification performance for each individual cover type is also a desirable attribute.

5.2.2 Classification Bias Correction

To evaluate the consistency and usefulness of the bias correction, a subset of Kansas counties was examined. This was not a random sample of Kansas counties as the first completed counties were used, but it was considered to be representative enough and large enough to determine: (1) if the accuracy achieved by the estimates which used training field performance matrices to calculate the bias is different from that achieved when test field performance matrices are used, (2) if error matrices can be extended to nonlocal recognition counties, and (3) whether correction for the bias increases the accuracy of the estimates by decreasing the difference from the SRS estimates.

To determine if the accuracy achieved by the estimates for which training field performance matrices were used to calculate the bias is different from that achieved when test field performance matrices were used, the variable considered was the difference between Landsat and SRS estimates. The test performed was a two-sample t-test for difference in the means between those counties for which training fields were used and those counties for which test fields were used to calculate the biases. The results were nonsignificant at the 25% significance level. It can be concluded that when test field performance is not available, the bias can be calculated by using the error performance matrix from the training fields.

Nonlocal recognition counties present another problem because there is no reference data from which a classification performance matrix can be obtained. Since statistics for the classification were extended from another county, it also seemed reasonable to extend the error matrix from the same county. To determine the validity of this extension, differences of Landsat estimates from SRS estimates for local counties were tested against the differences from SRS for nonlocal counties. This was accomplished by t-tests and the results showed that there was no difference ($\alpha = 0.25$) between the closeness of Landsat estimates to SRS for corrected local counties and for corrected nonlocal counties. It, therefore, seemed reasonable to calculate the bias correction for nonlocal recognition counties by the extension of an error matrix.

Two t-tests were used for quantitative evaluation of the bias correction. For local recognition counties, the corrected estimates for proportions and areas did not differ from the SRS estimates at the 25% significance level. On the other hand, the uncorrected estimates did differ from SRS estimates at the 25% level, indicating that correction for the bias brought Landsat estimates closer to the SRS hectares harvested. Hence, all the local recognition counties were corrected for bias by the method previously described.

For the nonlocal recognition counties, the bias correction also brought the Landsat estimates closer to the SRS estimates. There was a significant difference ($\alpha = 0.001$) from SRS in both proportion and area of wheat for the uncorrected estimates while the corrected estimates were not significantly different from the SRS estimates even at $\alpha = 0.25$. Therefore, all nonlocal county estimates were also corrected for classification bias.

In summary, we concluded that correcting for the bias is worthwhile since the difference of the corrected Landsat estimates from the SRS estimates is nonsignificant. Correction for the bias seems to be consistent between counties having test performance matrices and counties having only training performance matrices and is also consistent in extending error matrices to nonlocal counties. The same results were obtained for this part of the analysis regardless of whether the variable considered was proportion or area of wheat.

5.3 Wheat Area and Proportion Estimates

The estimates of hectares and proportions from the Landsat classifications on a county-by-county basis are presented in Table 12. Estimates for both proportion and area of wheat are given as the uncorrected and bias-corrected values. The values used in the statistical analysis were always the bias-corrected estimates.

5.3.1 Correlation of Landsat and USDA/SRS Estimates of Area and Proportion of Winter Wheat

The SRS estimates for proportion and area of wheat harvested are presented in Table 13 along with the corresponding Landsat estimates and their differences. The proportion and area estimates obtained from the Landsat classification are highly correlated with the USDA/SRS estimates. The correlation between Landsat and SRS wheat harvested proportions is $r = 0.77 \pm 0.05$ (Figure 21), while the correlation between Landsat and SRS wheat area estimates is $r = 0.80 \pm 0.04$ for harvested estimates (Figure 22). The correlation values are presented in standard error form which represents approximately a 68% confidence interval. These intervals are not exactly symmetric, but the furthest boundary has been presented here for simplicity [11].

5.3.2 Accuracy of Landsat Estimates

The accuracy of Landsat estimates of the area and proportion of wheat can be assessed at three levels: state,

Table 12. Uncorrected and bias-corrected Landsat estimates of hectares and proportions of wheat in Kansas.

COUNTY	LANDSAT UNCORRECTED ESTIMATES HECTARES	PROPORTION	LANDSAT CORRECTED ESTIMATES HECTARES	PROPORTION
	(000)	(%)	(000)	(%)
NORTHWEST DISTRICT				
CHEYENNE	93.5	35.1	82.6	31.0
DECATUR	55.7	23.9	31.4	13.5
GRAHAM	59.6	25.8	44.8	19.4
NORTON	70.1	30.8	50.3	22.1
RAWLINS	69.0	24.7	76.2	27.3
SHERIDAN	79.7	34.5	53.1	23.0
SHERMAN	46.8	17.1	25.8	9.4
THOMAS	45.6	16.5	22.6	8.2
TOTAL	520.0	25.8	386.8	19.2
NORTH CENTRAL DISTRICT				
CLAY	37.5	22.3	36.5	21.7
CLOUD	71.7	38.9	57.5	31.2
JEWELL	44.8	19.1	19.0	8.1
MITCHELL	83.4	44.9	86.7	46.7
OSBORNE	78.2	33.6	80.7	34.7
OTTAWA	54.3	29.0	53.5	28.6
PHILLIPS	44.9	19.3	17.9	7.7
REPUBLIC	68.8	36.9	52.6	28.2
ROOKS	81.4	35.4	72.2	31.4
SMITH	53.1	22.9	56.3	24.3
WASHINGTON	70.1	30.4	42.1	18.3
TOTAL	688.2	29.9	575.0	25.0
WEST CENTRAL DISTRICT				
GOVE	75.0	27.0	33.1	11.9
GREELEY	83.8	41.3	89.5	44.1
LANE	76.5	41.0	60.9	32.6
LOGAN	45.1	16.2	78.5	28.2
NESS	89.7	32.0	71.2	25.4
SCOTT	60.2	32.1	65.4	34.9
TREGO	85.5	36.6	60.3	25.8
WALLACE	36.3	15.4	61.3	26.0
WICHITA	58.6	31.2	58.4	31.1
TOTAL	610.7	29.5	578.6	28.0
CENTRAL DISTRICT				
BARTON	120.6	53.8	107.4	47.9
DICKINSON	84.9	38.3	91.5	41.3
ELLIS	117.3	50.3	108.2	46.4
ELLSWORTH	61.3	32.9	53.3	28.6
LINCOLN	62.5	33.2	54.5	28.9
MCPHERSON	104.2	44.9	103.9	44.8
MARION	69.5	28.0	68.5	27.6
RICE	105.3	56.4	95.2	51.0
RUSH	126.1	67.2	134.2	71.5
RUSSELL	67.6	29.5	56.8	24.8
SALINE	75.6	40.5	82.9	44.4
TOTAL	994.9	42.8	956.4	41.2